Technical Documentation for Health Resources Service Administration's Health Workforce Simulation Model

Health Resources and Services Administration

Bureau of Health Workforce

National Center for Health Workforce Analysis

The Health Resources and Services Administration (HRSA), U.S. Department of Health and Human Services (DHHS), provides national leadership in the development, distribution, and retention of a diverse, culturally competent health workforce that can adapt to the population's changing health care needs and provide the highest-quality care for all. The Agency administers a wide range of training grants, scholarships, loans, and loan repayment programs that strengthen the health care workforce and respond to the evolving needs of the health care system.

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Acronyms Used in This Report

ACA	Affordable Care Act
ACS	American Community Survey
ADA	American Dental Association
AHCA	American Health Care Association
AMA	American Medical Association
ACO	Accountable Care Organization
APN	Advanced Practice Nurse
BLS	Bureau of Labor Statistics
BRFSS	Behavioral Risk Factor Surveillance System
CBO	Congressional Budget Office
CDC	Centers for Disease Control and Prevention
CMS	Centers for Medicare and Medicaid Services
DHHS	U.S. Department of Health and Human Services
DHPSA	Dental Health Professional Shortage Area
ED	Emergency Department
FTE	Full Time Equivalent
HRSA	Health Resources and Services Administration
HPSA	Health Professional Shortage Areas
HWSM	Health Workforce Simulation Model
IPEDS	Integrated Postsecondary Education Data System
ISPOR	International Society for Pharmacoeconomics and Outcomes Research
LOS	Length of Stay
LPN	Licensed Practical/Vocational Nurse
LLTSS	Long Term Services and Support
MCBS	Medicare Beneficiary Survey
MEPS	Medical Expenditure Panel Survey
NAMCS	National Ambulatory Medical Care Survey
NCCPA	National Commission on Certification of Physician Assistants
NCES	National Center for Education Statistics
NCLEX	National Council Licensure Examination
NHAMCS	National Hospital Ambulatory Medical Care Survey
NHATS	National Health and Aging Trends Study
NHHCS	National Home and Hospice Care Survey
NHMDS	CMS's Nursing Home Minimum Data Set
NIS	National Inpatient Sample
NLN	National League for Nursing
NMW	Nurse Midwife
NNHS	National Nursing Home Survey
NP	Nurse Practitioner
NPI	National Provider Identification
NPPES	National Plan and Provider Enumeration System
NSSRN	National Sample Survey of Registered Nurses
OES	Occupational Employment Statistics
PA	Physician Assistant
RN	Registered Nurse
SNF	Skilled Nursing Facility

I. Introduction

The Health Workforce Simulation Model (HWSM) is an integrated microsimulation model that estimates the future demand for and supply of health care workers in multiple professions and care settings. The model was designed to produce national and state-level estimates and to quantify the effects of policy options and trends affecting care use and delivery.

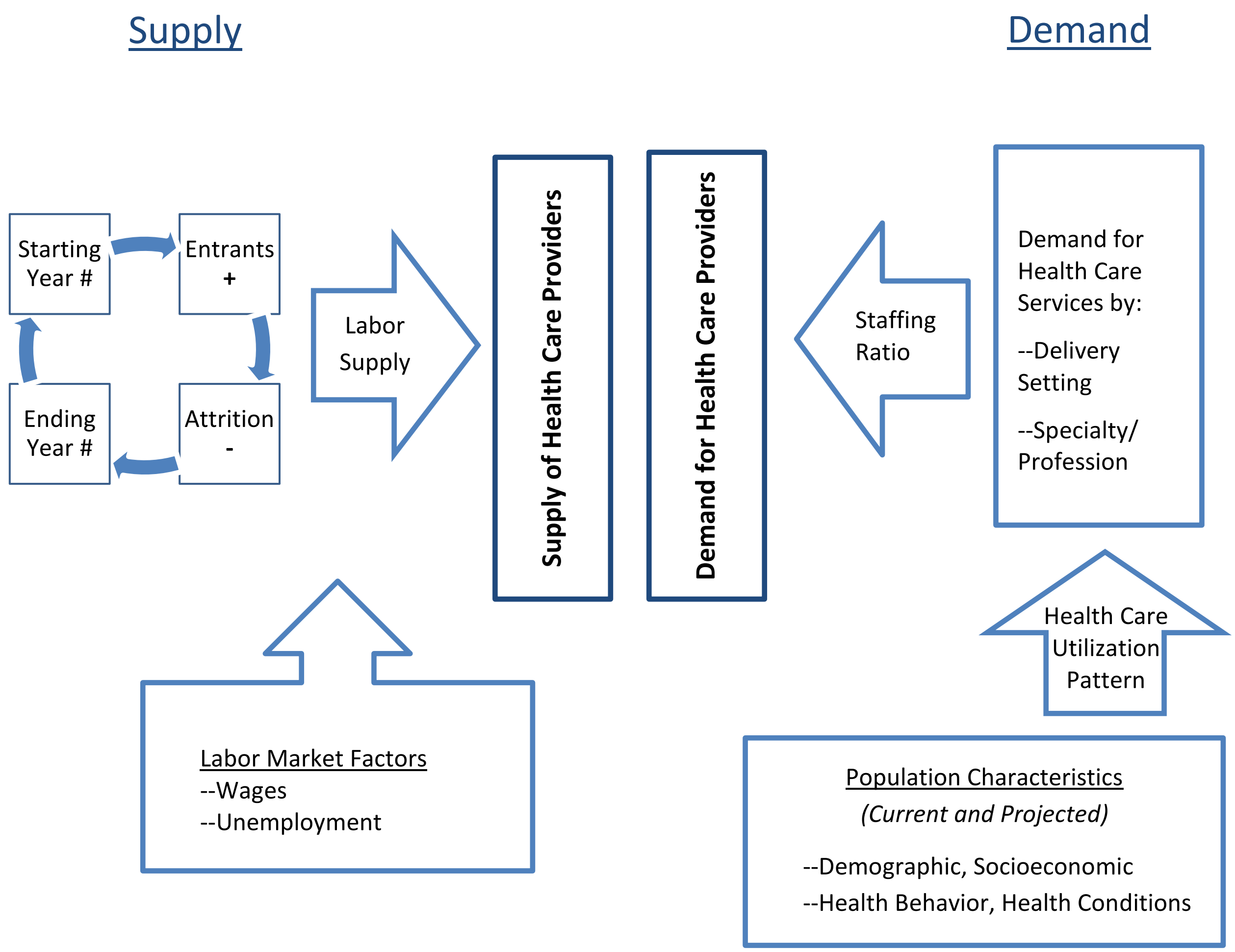
This report documents the logic, methods, data, assumptions, and validation processes for HWSM in general, and as applied to individual health professions. HWSM continues to be maintained and refined—including new professions added to the model and scenario modeling capabilities enhanced. Each year the model is updated with the most recent data from key data sources, so recently modeled professions use more current data than professions modeled in previous years.

The remainder of this chapter provides an overview of HWSM supply and demand components and the health professions modeled to date. Chapter II describes in more detail the general components of the supply model, and Chapter III describes the demand model. Chapter IV provides information specific to the modeled health professions. Chapter V describes model strengths, limitations, and validation activities.

While the nuances of modeling differ for individual health professions and medical specialties, the basic framework used within HWSM remains the same and consists of three components: 1) the **model for supply of health professionals**, 2) the **model for demand for health care services**, and 3) the **staffing patterns** that convert demand for services to demand for health care workers (Exhibit 1). Consistent with prevailing practice, the model assumes that national supply equals demand in the base year unless there is evidence of national imbalances between supply and demand.[1] To project the number and characteristics of future health care workers and service users, HWSM simulates individual-level data based on predicted probabilities estimated from recent data. Depending on the predicted probabilities, individual records are simulated to age forward. The aged individual-level records are then aggregated to obtain the national or state-level projections. On the service use side, the current utilization rates by individual characteristics are applied to projected populations at the national and state levels.

[1] Ono, T., Lafortune, G., Schoenstein, M. 2013. "Health workforce planning in OECD countries: a review of 26 projection models from 18 countries". *OECD Health Working Papers, No. 62*. France: OECD Publishing 2013:8-11

Exhibit 1: HRSA's Health Workforce Simulation Model



Multiple elements contribute to the development of the model (Exhibit 1). To calculate supply, workforce decisions for future professionals are simulated based on provider characteristics (demographics, education level for registered nurses), profession and specialty, and the features of the state or national economy (wages, general unemployment rate). The major components of the **supply model** include:

1. A micro data file containing the characteristics of the current workforce in a given profession.
2. Estimates of the annual number and characteristics of newly trained workers entering a given profession.
3. Equations that describe workforce decisions, such as retirement and number of hours worked, based on characteristics of the workforce and current labor market factors.

Predicted probabilities from these equations simulate labor supply decisions of future health care professionals.

HWSM simulates the demand for health care services based on individual characteristics of the U.S. population (demographics, socioeconomics, health behavior, and health status). Major components of the **demand model** are:

1. A database that contains characteristics for each person in a representative sample of the current and projected population in each state over time (the most recent updates are through 2030).
2. Regression equations that relate health care use patterns by setting to a person's characteristics. Predicted probabilities from these equations are applied to simulate health care utilization of future populations.
3. Workforce **staffing patterns** that translate demand for health care services into projected demand for full time equivalent (FTE) providers by profession and care delivery setting.

HWSM simulates demand for health care services in seven settings (emergency departments, hospital inpatient, provider offices, outpatient departments, home health, nursing homes, and residential facilities). Demand for specific services within a setting is combined with provider staffing ratios in that setting to estimate the demand for health care providers.

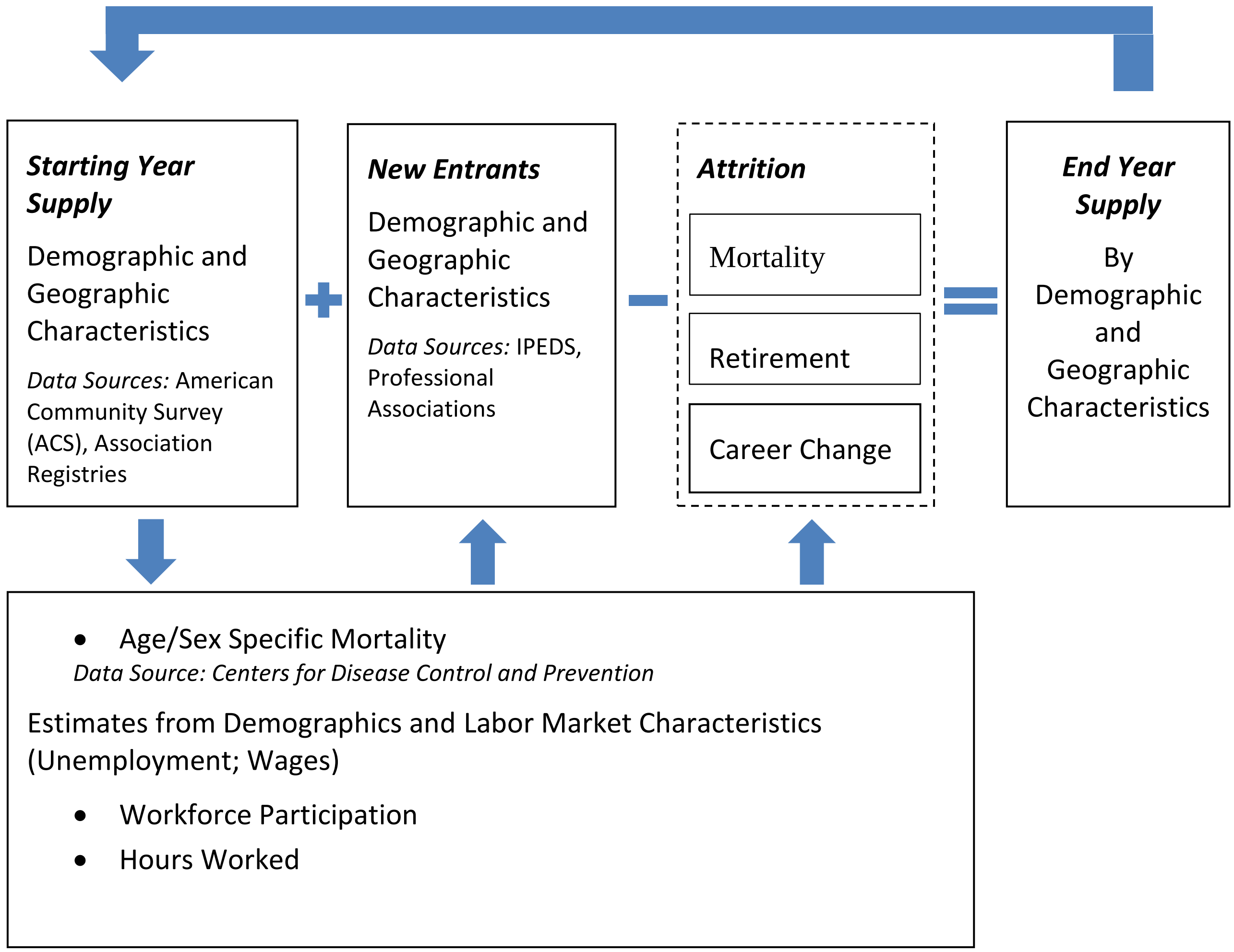
Consistent with recommended standards,[2] HWSM consists of self-contained modules that describe different components of the health care system. HWSM runs using SAS (Statistical Application Software).

II. Modeling Supply of Health Professionals

The supply component of HWSM links individual and labor market characteristics to health care workers' labor supply decisions (Exhibit 2). After the base year data are trended forward one year, those estimates become the starting point for the subsequent year and the process depicted is repeated annually over the projection period.

[2] Citro CF and Hanushek EA. 1991. Improving Information for Social Policy Decisions: The Uses of Microsimulation Modeling – Volume I: Review and Recommendations. Washington, DC: National Academy Press. A condensed version of this report entitled: Microsimulation Models for Social Welfare Programs: An Evaluation, is available at http://www.irp.wisc.edu/publications/focus/pdfs/foc153b.pdf

Exhibit 2: Flow Diagram for the Supply Component of HWSM



A. Estimating Base Year Supply of Active Health Professionals

The base year supply database in HWSM contains unique records representing each person in the health workforce in the base year. For professions (e.g., physicians, dentists, physician assistants) which have national registries with robust data describing individual characteristics, these registries were used.

For professions (e.g., nursing[3], technologists and technicians) where the base year supply data are estimated from surveys, records for each survey participant were replicated according to their sample weight in the survey file. For example, if a person's record in the American Community Survey (ACS) has a sample weight of 100 (indicating that it represents 100 people in that

[3] For registered nurses and licensed practical nurses, some states provided data from licensure files and for all other states the starting supply data come from the American Community Survey.

particular profession), 100 identical records were created. Creating a record for each person is important because unique probabilities associated with labor force decisions are used for each simulated person. In states with smaller population, where the sample size is small, the creation of multiple records helped “smooth” the impact of individual characteristics on labor supply decisions such as retirement. For these smaller states, samples were drawn not only from that small state but from the state’s Census District.

All the professions modeled use individual characteristics (age and sex, and sometimes race-ethnicity) to model labor force decisions. There are some nuances by profession (for example, education level is modeled for nurses), and such nuances are described in chapters covering specific professions. Some professions also use labor market characteristics associated with their particular state from the Bureau of Labor Statistics (BLS), namely overall state unemployment rate and average professional wages, as inputs to modeling labor force participation.

HWSM baseline supply projections assume

- *Current age and sex distribution of new entrants will be retained in the future*
- *Current patterns of retirement and hours worked will remain unchanged within a given age and sex group*

B. Modeling New Entrants to the Workforce

Data used to estimate the number and characteristics of new entrants depend on the profession being modeled; see Chapter IV for discussions by profession. Baseline estimates on the number and characteristics of new entrants in each profession over the forecast period are made under the assumption that current patterns continue throughout the projection period.

The mechanism for simulating new entrants to the workforce was done via the creation of a “synthetic” cohort based on the number and characteristics of recent entrants in each profession. First, HWSM derived the probability of an individual having age and gender from the base year distribution of those characteristic in the population of new entrants. HWSM then created a record for each new entrant and generated a series of random numbers. Depending upon the value of the random number and the probability of having a particular characteristic, the individual was assigned that characteristic.

C. Modeling Labor Supply of Health Care Workers

HWSM estimated the labor supply of individuals in a profession using a three-step process:

1. The probability that a person would be alive.

2. The probability that a person was active in the profession.

3. The estimated Full Time Equivalent (FTE) supply, based on predicted hours per week for each person divided by 40. Prior to 2017, one FTE was defined as the *current average number of hours worked per week* for those who are active in the profession. Depending upon data availability, for some professions hours worked reflect total professional hours, while for other professions hours worked reflect patient care hours.

Estimates specific to a profession or medical specialty were generally used. However, for some professions and specialties with small sample size and other data limitations, information on occupational categories or similar medical specialties were used in place of profession-specific data. Also when patient care hours were not available, the proportion of clinician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time.

The basic assumption underlying the baseline supply projections was that the current patterns of retirement and hours worked remained unchanged within a given age group and sex and that current age and sex distribution of new entrants to the profession was maintained. Under this scenario, supply changes over time were due solely to the changing demographic composition of the workforce and number of new workers trained. Supply scenarios modeled the sensitivity of projections to assumptions regarding numbers trained, retirement patterns, and hours worked patterns.

1. Probability of Being Alive

The probability of being alive was determined from mortality rates by age and sex obtained from the Centers for Disease Control and Prevention (CDC), and accounted for the fact that age-adjusted mortality rates through age 65 for professional and technical occupations are approximately 25 percent lower than overall national rates for men and 15 percent lower for women.[4,5]

2. Workforce Participation

Workforce participation probabilities for nurses, physicians, advanced practice nurses [APNs], and physician assistants [PAs] were modeled using survey or licensure data which sources are

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[4] Arias E. 2012. "United States life tables, 2008." *National vital statistics reports* vol 61 no 3. Hyattsville, MD: National Center for Health Statistics.

[5] Johnson NJ, Sorlie PD, Backlund E. 1999. "The impact of specific occupation on mortality in the U.S. National Longitudinal Mortality Study". *Demography*; 36:355-367.

described in the individual chapters covering each profession. For all other professions modeled, the probability that the person is actively employed in the health profession was modeled using estimates derived from the ACS.

Because the ACS does not list the profession of individuals who have been retired for more than five years, profession-specific labor force participation rates were imputed for workers over age 50—many of whom may have retired more than five years ago. For these individuals who had been employed at some time during their adult life, we used two approaches that are described in more detail in individual profession chapters. Earlier work used activity rates based on level of education (less than baccalaureate, baccalaureate, or graduate degree) as a proxy for retirement patterns of health workers with similar education level. More recent analyses modeled net changes in the age distribution of older workers in each profession to calculate probability of exiting the workforce. The actual approach used for each profession is discussed in individual profession chapters.

People sometimes change professions or further their education to enhance career opportunities. When this happens, HWSM treats these as exits from the original profession and entrants to the new profession. Data limitations did not allow this aspect to be built into HWSM. The only profession for which career progression is built into HWSM is nursing (discussed in Chapter IV) that allows progression from licensed practical nurse [LPN] to registered nurse [RN], and from RN to APN).

3. Hours Worked and FTE Supply

Ordinary Least Squares regressions on 5-year ACS data files were used to derive the expected number of hours worked in a week by each individual active in the profession.6 Explanatory variables included age, sex, log of hourly earnings, the overall unemployment rate, and a year indicator. Race and ethnicity recently were added as explanatory variables for modeling RNs and LPNs using the following four categories: non-Hispanic white, non-Hispanic black, non-Hispanic other, and Hispanic. Profession-specific wage and unemployment rates data were taken from the BLS and were included as time varying covariates. The estimate of hours worked was divided by 40 to obtain the FTE supply of each year. Prior to 2017, the base year estimated average number of hours worked for the profession was used as the measure of one FTE. Then for each subsequent year, the estimate of hours worked was divided by the average number of hours worked per week at baseline to obtain the FTE supply.

[6] Some professions are based on 2006-2011 ACS data; the recent update of the model for RNs and LPNs used 2010-2014 ACS data.

The approach for modeling physician supply was different, and relied on survey data as described in Chapter IV.

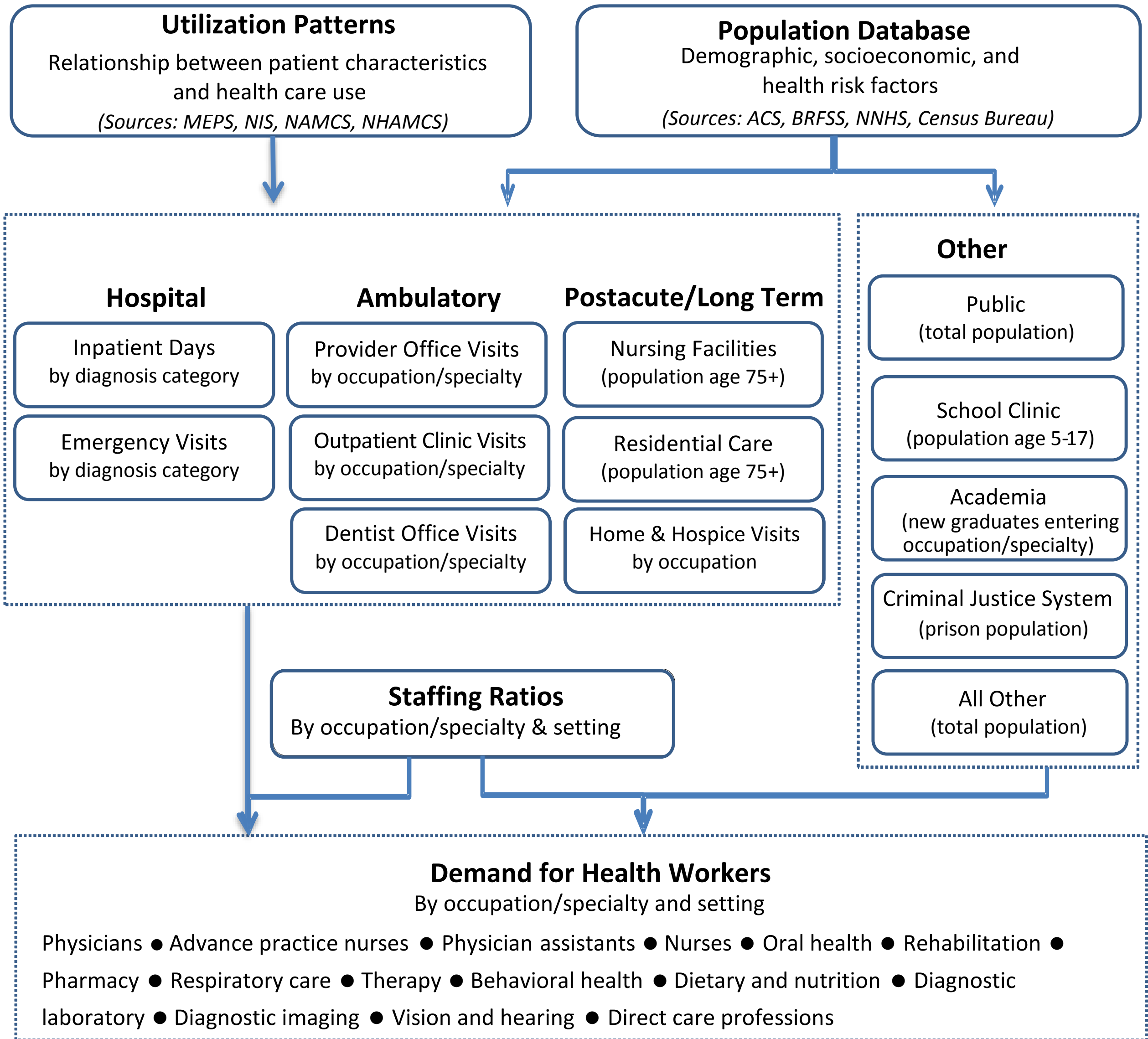
III. Modeling Demand for Health Care Services and Providers

The HWSM models demand using three major elements:

1. *Databases* that contain demographic, socioeconomic, health status and health behavior information for a representative sample of the baseline and projected populations.
2. *Regression equations* relating an individual's demographic, socioeconomic, health status and health risk factors to health service utilization by both care delivery setting and medical profession/specialty.
3. *Staffing **patterns*** that convert demand for services to demand for providers.

Exhibit 3 presents a flow diagram for the demand component of HWSM, although not all care delivery sites pertain to every health profession modeled. The next section provides information on the creation of the baseline micro *database* representative of the entire U.S. population, followed by the specifications of *regression equations* connecting individual characteristics to service utilization. *Staffing pattern models,* which are combined with projected service use to generate estimation of *provider requirements,* are then described.

Exhibit 3: Flow Diagram for the Demand Component of HWSM



Sources: MEPS=Medical Expenditure Panel Survey; NIS=National Inpatient Sample; NAMCS=National Ambulatory Medical Care Survey; NHAMCS=National Hospital Ambulatory Medical Care Survey; NHATS= National Health and Aging Trends Study; ACS=American Community Survey; BFRSS=Behavioral Risk Factor Surveillance System; MCBS=Medicare Beneficiary Survey; population projections come from states and the U.S. Census Bureau.

A. Construction of the Baseline and Projected Population Databases

The microsimulation approach—where demand for health care services is modeled separately for individual people—requires individual level (micro) data on the predictors of health care use for each person in a representative sample in a designated geographic (national, state, or sub-state). The core micro data file that forms HWSM's baseline population was the American Community

Survey (ACS) from the most recent single year ACS data.[7] However, while ACS provided demographic and socioeconomic characteristics of a representative sample of the population in each state, it lacked health status and health behavior variables that impact the demand for health care services. The individual "profile" required in this model included health status variables (e.g., diabetes and cardiovascular disease), and health-related behavior (e.g., obesity, smoking) in addition to, demographic information and socioeconomic characteristics.

Explanatory Variables Used in Demand Models

Demographics

1. *Children (ages 0-2, 3-5, 6-13, 14-17 years)*
   Adults (ages 18-34, 35-44, 45-64, 65-74, 75+ years)
2. *Sex (male, female)*
3. *Race/ethnicity (non-Hispanic white, non-Hispanic black, non-Hispanic other, Hispanic)*

Health-related lifestyle indicators

4. *Body weight status (unknown, normal, overweight, obese)*
5. *Current smoker status (Yes, No)*

Socioeconomic conditions

6. *Household annual income (<$10,000, $10,000 to <$15,000, $15,000 to < $20,000, $20,000 to < $25,000, $25,000 to < $35,000, $35,000 to < $50, 000, $50,000 to < $75,000, $75,000+)*
7. *Medical insurance status (private, public, self-pay)*

Chronic conditions

8. *Arthritis, asthma, cardiovascular disease, diabetes, hypertension*
9. *History of heart attack or stroke*

Geographic location

10. *State (or county)*
11. *Metropolitan area*

Therefore, to create the baseline micro data file, other publicly available survey-based data sources were combined with the ACS— the Behavioral Risk Factor Surveillance System (BRFSS), the Medicare Beneficiary Survey (MCBS), and CMS's Nursing Home Minimum Data Set (NHMDS).

The total number of people living in nursing homes and residential care, by state and age group, was constructed to match published numbers from the CDC.[8] A sample of approximately 1.3 million nursing home residents and 687,000 individuals living in residential care was merged with the ACS to construct a representative sample of the population residing in nursing homes and residential care facilities. The remaining ACS participants living in communities were matched with the BRFSS.

Behavioral Risk Factor Surveillance System

[7] The 2015 ACS file was used to model demand for LTSS. The 2014 ACS file was used to update RN and LPN nursing projections. The 2013 ACS file was used to develop the recent workforce projections for behavioral health occupations, paramedics and EMTs, physicians, advanced practice nurses, and physician assistants. The 2011 ACS was the most recent file available when the other health professions were modeled (e.g., technicians, therapists, and dental hygienists and assistants).

[8] National Center for Health Statistics. Long-Term Care Providers and Services Users in the United States: Data from the National Study of Long-Term Care Providers, 2013 – 2014. February 2016. Available at: http://www.cdc.gov/nchs/data/nsltcp/2014_nsltcp_state_tables.pdf

Population data are projected under the assumption that the prevalence rates of health behavior and health conditions by demographic groups do not change (although scenarios model the implications if prevalence of health conditions do change within demographic groups)

The BRFSS, administered annually by the CDC, collects data on a sample of over 500,000 individuals. Similar to the ACS, the BRFSS includes demographics, household income, and medical insurance status on a stratified random sample of households in each state. The BRFSS also collects detailed information on the presence of chronic conditions and other health risk factors (e.g., obesity, smoking). The two most recent BRFSS files were combined to create a joint file with approximately one million records.[9]

Medicare Beneficiary Survey: Starting in 2017 with the long term services and support (LTSS) workforce analysis, the health characteristics of the residential care population were modeled using individuals from the MCBS who live in residential care facilities (with the 2013 MCBS data being the most recent available). Prior to 2017, individuals living in residential care were merged with the BRFSS—thus taking on the health risk profile characteristics of a community-based population that is healthier, on average, than the population in residential care facilities.

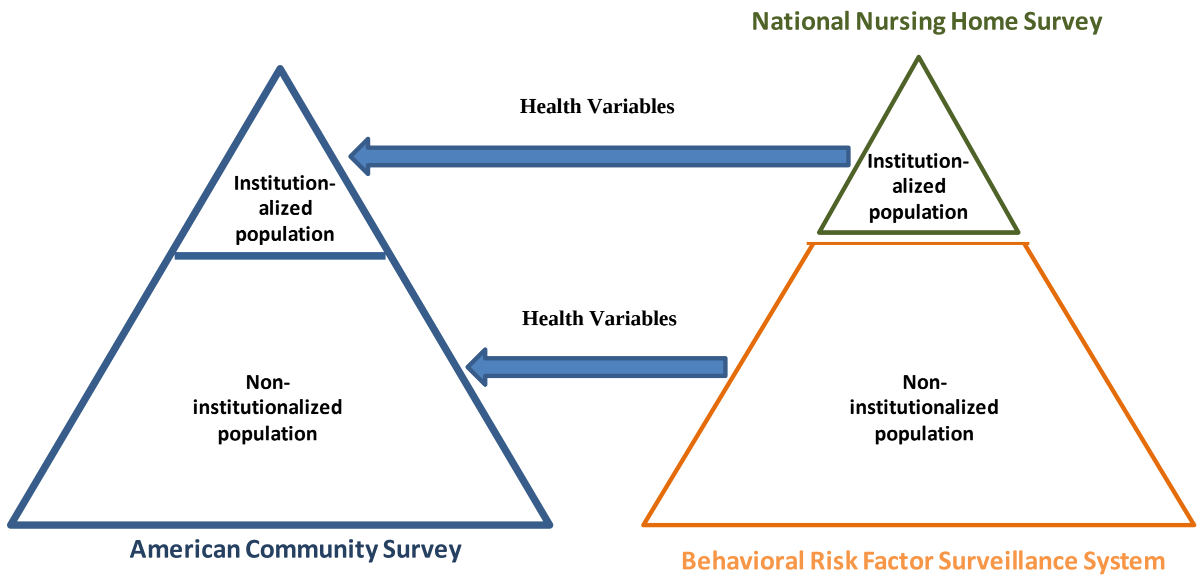
CMS's Nursing Home Minimum Data Set (NHMDS): Starting in 2017with the LTSS workforce analysis, we used the NHMDS to develop a representative sample of residents in nursing homes in each state. This data source contains information on disease prevalence and health risk factors for each person residing in a nursing home. From the NHMDS we drew a random sample of resident records where the size of each sample was determined based on CMS published data of the average number of nursing home residents in each state by age group.

The HWSM population database used a statistical matching process that combined patient health information from the different files with the larger ACS file that had a representative population in each state (and for some sub-state levels). As illustrated in Exhibit 4,using information on residence type the ACS population was stratified into those residing in nursing facilities (matched to people in the NHMDS), those living in residential care facilities (matched to people in the MCBS who also live in residential care), and individuals residing in the community (matched to people in the BRFSS).

[9] The combined 2011 and 2012 BRFSS files were used for nurses, technicians, therapists, oral health (and other occupations). The workforce projections for physicians, behavioral health, and other recently modeled occupations used the combined 2011 and 2013 BRFSS files (omitting the 2012 file which lacked information on hypertension). In November, 2015, IHS combined the two latest BRFSS files (2013 and 2014) to create a joint file with more than one million individuals.

For the non-institutionalized population, each individual in the ACS was matched with someone in the BRFSS from the same sex, age group (15 age groups), race, ethnicity, insured/uninsured status, household income level (8 income categories), and state of residence.[10] Individuals categorized as residing in a residential care facility or nursing home were randomly matched to a person in the MCBS or NHMDS, respectively, in the same state, age group, sex, and race and ethnicity strata.

Exhibit 4: Population Database Mapping Algorithm



Developing demand forecasts for future years required the creation of micro-level data sets for future populations. This was done by assigning new sample weights to ACS respondents so that when these weights were applied, the file produced population estimates that mirrored Census Bureau projections by demographic groups (age group, sex, race and ethnicity)[11] at the national level and population projections estimated by state governments. The model's Baseline Scenario assumed that base year prevalence rates of health and health behavior characteristics remained

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[10] The first round of BRFSS-ACS matching produced a match in the same strata for 93% of the population. To match the remaining 7%, the eight income levels were collapsed into four (1% matched), then the race/ethnicity dimension was dropped (2% matched), and then the same criteria as the first round was applied except State was removed as a strata (remaining 4% matched).

[11] U.S. Census Bureau. 2012. *National Population Projections 2012 to 2060 (based on 2010 Census)*. http://www.census.gov/population/projections/data/national/2012.html. Later updated to the 2014 series population projections to model demand for physicians, behavioral health, and other recently modeled health professions. Available at http://www.census.gov/population/projections/data/national/2014.html

the same by age, sex, race and ethnicity in the projected years—though we modeled scenarios where disease prevalence and disability rates declined within demographic strata.

Demand projections have tried to quantify the health care use and health workforce implications of insurance expansion under the Affordable Care Act (ACA). Sources for estimates of insurance expansion include national projections from the Congressional Budget Office (CBO),12 as well as state-level estimates published by the Urban Institute (and were scaled to be consistent with the most recent national estimates).13 The Urban Institute's state-level estimates were then distributed across the projected population in a state, using predicted probabilities from a logistic equation with demographic, socioeconomic, and health risk factors as explanatory variables. Those who were predicted to be uninsured were assigned the probability of gaining coverage based on the Urban Institute's proportions. While national and state policy continues to evolve and the future of insurance expansion is unclear, for the latest workforce projection covering the LTSS workforce insurance expansion has little impact on workforce demand (as the large majority of patients using LTSS service qualify for Medicare, Medicaid, or are dually eligible.

B. Modeling Demand for Health Care Services

This section documents the development of regression equations used to estimate health care use by settings and the health care use measures that constitute the dependent variables in the regression equations (see Exhibit 5 for list). Exhibit 6 lists the population groups used to estimate the demand for health care services that depend on the population size of potential users.

[12] Congressional Budget Office 2012. *Estimates for the insurance coverage provision of the Affordable Care Act. Updated for the recent Supreme Court decision*. Available at: http://www.cbo.gov/sites/default/files/cbofiles/attachments/43472-07-24-2012-CoverageEstimates.pdf . Later updated to: Congressional Budget Office. Insurance Coverage Provisions of the Affordable Care Act—CBO's April 2014 Baseline; Table 2. Available at: https://www.cbo.gov/sites/default/files/cbofiles/attachments/43900-2014-04-ACAtables2.pdf

[13] Urban Institute 2010. *How would states be affected by health reform?* Available at http://www.urban.org/UploadedPDF/412015_affected_by_health_reform.pdf.. Urban Institute periodically updates estimates for select states. Therefore, we periodically update our estimates in the demand model to be consistent with Urban Institute estimates. Updated (2014 #s) coverage estimates for select states. Available at: http://www.urban.org/UploadedPDF/413036-The-Launch-of-the-Affordable-Care-Act-in-Selected-States-Coverage-Expansion-and-Uninsurance.pdf

Exhibit 5: Care Delivery Settings and Health Care Use Measures

Care Delivery Setting and Service Type	Health Care Use Measures
Ambulatory care	
Physician and other provider offices	Total visits, visits by provider type and specialty; Rx scripts
Outpatient departments and clinics [a]	Total visits, visits by provider type and specialty; Rx scripts
Dental offices	Dental (non-cleaning), dental cleaning, and orthodontic visits
Hospital inpatient and emergency care	
Hospital inpatient (includes skilled nursing facility (SNF) units of hospitals)	Hospitalizations and length of stay overall, and by primary diagnosis (ICD-9); Rx scripts
Hospital emergency department	Emergency visits by primary diagnosis (ICD-9); Rx scripts;
Post-acute care and Long term care	
Home Health/Hospice	Total visits by provider type

Note: [a] Examples of outpatient clinics include well-baby clinics/pediatric outpatient departments; obesity clinics; eye, ear, nose, and throat clinics; family planning clinics; cardiology clinics; internal medicine departments; alcohol and drug abuse clinics; physical therapy clinics; and radiation therapy clinics.

Exhibit 6: Care Delivery Settings and Potential Users that Drive Demand

Care Delivery Setting and Service Type	Potential Users
Post-acute care and Long term care	
Nursing home (includes free standing SNF)	Prevalence varies by demographic group
Residential care facilities	Prevalence varies by demographic group
Other Settings	
Educational institutions	Number of professionals trained
Public/community health	Total population
School Health	Population aged 5-18 years
All Other	Total population

1. Estimating Health Care Use

Health seeking behavior was generated from econometrically estimated equations using data from the Medical Expenditure Panel Surveys (MEPS).[14] Five years of data were pooled to provide a sufficient sample size for regression analysis.

Regression analyses on baseline data yielded predicted probabilities of health care use, stratified by demographic groups, care delivery settings, and types of service, the predicated probabilities were then applied to the projected population.

To model the impact of expanded medical coverage under health care reform on health care use, it was assumed that a newly insured person would use health care services at the same rate as a person with private insurance of similar demographic, health status, health risk, and economic

[14] The 2007-2011 MEPS files were analyzed for modeling demand for nurses technicians, therapists, oral health, and select other health occupations. The 2008-2012 MEPS files were analyzed for modeling behavioral health professions and to update projections for physicians, APNs and PAs. The 2009-2013 MEPS files were used to update the nurse workforce demand projections. The 2010-2014 MEPS files were used to model demand for long term care workers. The combined 5-year files contain data on approximately 170,000 individuals.

characteristics. Baseline demand scenarios assume current patterns of care use continue into the future, controlling for changing demographics. Alternative scenarios described later make different assumptions regarding care use patterns under emerging care delivery models.

Health care utilization projections methodology in HWSM assumes:

- *The current pattern of health care use by demographic and health risk groups will be retained.*
- *Newly insured individuals from health care reform will have utilization patterns similar to other insured persons who share the same demographic and health risk characteristics.*

2. Ambulatory Medical Care Services

MEPS data were used to quantify the relationship between patient characteristics and number of annual office/clinic visits or hospital outpatient department visits with a provider of a particular profession or specialty. In addition to physicians, MEPS contains data on visits to many types of providers, including physician assistants, nurse/nurse practitioners, dentists, optometrists, opticians, physical therapists, and occupational therapists.

Annual visits by profession or specialty were estimated using Poisson regression. Explanatory variables were age group, race/ethnicity, smoking status, body weight category, presence of chronic conditions (diagnosed with arthritis, asthma, coronary heart disease, diabetes, or hypertension; history of cancer, heart attack, or stroke), insurance type, household income level, residence in a metropolitan area, and MEPS survey year. Enrollment in a managed care plan was added as an explanatory variable for later work on physicians, APNs, PAs, and behavioral health professionals in 2014.

MEPS reports the highest trained person seen during an ambulatory visit. Consequently, if a patient had a visit to a physician, the MEPS survey did not indicate whether the patient also saw other health professionals during the course of the visit. Predictive equations were developed from the National Ambulatory Medical Care Survey (NAMCS) to determine the likelihood that a patient would see additional health professionals (e.g., registered nurse (RN) or NP, licensed practical/vocational nurse (LPN), or PA) during a clinical visit. In addition, data from NAMCS were used to determine the number of prescriptions that were generated during an ambulatory care visit-which was then used in the demand projections for pharmacy-related professions.

a) Hospital Inpatient and Emergency Services

Demand for hospital inpatient and emergency services use the five latest years of MEPS files, along with the latest National Inpatient Sample (NIS) and National Hospital Ambulatory Medical

Care Survey (NHAMCS) files.[15] Multiple years of MEPS data were used to increase the size of the sample and provide reliable estimates for hospitalization and emergency department (ED) visits by medical and surgical conditions. Additional information on the data and methods for modeling demand for hospital inpatient and emergency services are described below.

(1) Hospital Inpatient Services

Utilization patterns of inpatient services by individual characteristics were modeled in two parts:

1. The probability that an individual would experience a hospitalization.
2. The expected length of stay for that hospitalization.

The probability of hospitalization in general, acute care, long term or specialty hospitals was modeled using data from MEPS. ICD-9 codes for hospitalizations recorded in MEPS were categorized in 28 broad specialty groupings to identify which specialty services were provided. Logistic regression estimated the probability of hospitalization based on patient age group, sex, race, ethnicity, insurance type, presence of diabetes among the diagnosis codes, and residence in a metropolitan area.

Using discharge records from the NIS, Poisson regressions generated the expected number of days spent or length of stay (LOS) in the hospital, conditional on a hospitalization for each medical and surgical condition. Because of the large sample size of NIS (over 8 million hospital stays), estimates derived from NIS were stable even for hospitalizations for rare conditions. Expected LOS calculated from NIS was applied to the individuals in the population database who were predicted to experience a hospitalization, so HWSM was able to simulate each person's expected number of inpatient days during the year for different types of medical or surgical conditions. The NIS was also used to determine the expected number of prescriptions that would be filled by hospitalized individuals.

(2) Hospital Emergency Department Services

Modeling demand for emergency services consisted of two components:

1. The probability that a person with given characteristics would have an emergency visit.
2. The types of services that the person would receive. The types of services included specialty consults, services from non-physician clinicians, and prescriptions.

MEPS data on annual hospital ED visits were used to determine the ED service use in the population for 20 categories of services, with ICD-9 codes for ED visits recorded in MEPS used

[15] Nurses, physicians, technicians, therapists, and select other health occupations used the 2010 NIS and NHAMCS files prior to the 2013 NIS and 2012 NHAMCS becoming available.

to identify which specialty services were provided during an ED visit. Logistic regressions estimated the predicted probability that a person with given characteristics would have an ED visit during the year by specialty service.

However, MEPS does not identify the medical specialty of the providers and it lists only the highest level of provider seen. Therefore, the NHAMCS was used to identify the types of services that typically accompany an emergency visit for a particular category of services (namely, medications prescribed and lab tests or exams performed), and the probability that another provider was seen (e.g., physician, PA, RN/NP or LPN).

b) Post-Acute and Long Term Care Settings and Services

Within post-acute care settings, HWSM modeled the demand for home and hospice care services. Demand for post-acute care in hospitals and SNFs that are a part of a hospital were modeled as inpatient services. Freestanding SNFs were modeled as nursing facility stays (see Exhibit 3).

(1) Home Care Visits

The pooled 5-year MEPS files (n~22,000) were used to model home visits. The files contained annual use of home health services (including information on the types of health care workers providing home health services), reasons for home health care, and type of services provided. Various therapists also provided care during visits, and a relatively small number of visits were listed as hospice visits (with no provider type specified). Home visits not related to health providers (e.g., companion, homemaker), providers with very few visits (e.g., dietitian, IV therapist, physicians), and visits where the type of provider was unclear (e.g., skilled, non-skilled, other) were excluded.

Poisson regressions were used to determine the expected number of annual visits by each provider type. Explanatory variables included patient demographics, socioeconomic characteristics, medical insurance type, health related behavior, and presence of chronic conditions.

(2) Nursing Facility and Residential Care Stays

Creation of the population file for nursing homes and residential care facilities was described previously—using the CMS Nursing Home Minimum Dataset and respondents in residential care in the Medicare Beneficiary Survey. The Baseline Scenario demand projections assume the continuation of rates of nursing home and residential care within each demographic stratum (by age, sex and race/ethnicity). Prior to modeling the LTSS workforce in 2017, growth in the population age 75 and older was used as a proxy for growth in the demand for nursing facility and residential care facility workers

> *Staffing Ratios are determined by assuming that*
>
> - *The current demand for services in each setting is met by the current supply of professionals in those settings*
> - *Staffing ratios remain constant through the projection period*

c) *Other Settings Where Health Care Professionals Work*

Some health care providers, such as nurses and counselors, provide services in schools, the military, and the community as public health providers. In addition, some health care professionals are engaged in teaching and preparing new entrants to the workforce. There are no survey data that capture the demand for these services. Therefore, demand was based on the expected number of individuals who would likely use such services (Exhibit 6). For example, the demand for school-based services was derived by HWSM directly from the projected size of the population of school-aged children.

3. Staffing to Meet Demand for Health Care Services

This section discusses the assumptions and methods used to convert demand for health care services into demand for providers. Services provided (e.g., visits, hospitalizations, procedures, or prescriptions written) or demand drivers for services for which there are no survey data (e.g., total population and school aged children) were compared with the number of providers working in the setting. For professions that provide services across a wide array of setting (e.g., nurses and therapists), information on the employment distribution of the care providers in the base year from the BLS was used to determine the number of individuals working in each setting.

Assuming that the base year demand for services in each setting was fully met by the available professionals in that setting, the base year staffing ratio was calculated by dividing the national volume of service used by the number of health care professionals employed in each setting. For professions that provide services in a single setting, base year utilization was divided by the base year supply to derive the staffing ratio for that profession. The staffing ratio was then applied to the projected volume of services to obtain the projected demand for providers in every year after the base year.

The baseline scenarios in HWSM assumed that care delivery patterns remained unchanged over time given the demand for health care services. However, the number and mix of health professionals required to provide the level of health care services demanded is influenced by how the care system is organized and care is reimbursed, provider scope of practice requirements, economic constraints, technology, and other factors. Emerging health care delivery models and advances in technology may alter health care delivery in the future, changing the relationship between patient characteristics and the probability of receiving care in a particular setting. The staffing ratios would also change under new care delivery models. Over time, additional scenario modeling capabilities have been built into HWSM. Scenarios modeled for physicians, APNs and PAs that explore how care use and care delivery patterns might change include: (1) greater enrollment in risk-bearing plans such as managed care or Accountable Care Organizations (ACOs), (2) greater use of health information technology that allows for productivity gains and some delegation of work from specialists to generalists and from physicians to non-physicians, and (3) greater use of retail clinics where care is predominantly provided by NPs and PAs. Scenarios modeled for nurses and the long term care workforce include greater preventive care around reducing excess body weight, smoking cessation, and improved control of blood pressure, cholesterol levels, and blood glucose levels.

IV. Application of HWSM to Project Supply and Demand for Specific Occupations

Although the HWSM structure, as described in the previous sections of this document, is consistent across occupations, some input data or assumptions vary by occupation. This section presents occupation-specific information about the estimation process.

A. Long Term Services and Support Model (updated 2017)

This section contains a description of the data, assumptions, and methods used to adapt HWSM to model the sector-specific LTSS workforce. The settings included under LTSS are nursing homes, residential care facilities, home health, hospice, and adult day services centers. Because of data limitations, home health and home-based hospice visits are combined into home care. MEPS data does not distinguish between home health visits associated with chronic care management and visits following hospital discharge for acute conditions.

1. Estimating Base Year Supply for LTSS Occupations

HWSM supply projections focus on occupations with high education requirements which often create time lags in training new workers, and for which information on future adequacy of supply can help mitigate supply inadequacies. Such occupations usually require a license, and licensing databases often can provide estimates of the current year supply. Licensure data is unavailable for direct care workers, however, and for many health occupations there is no centralized location to obtain licensure data. Rather such data would need to be obtained from individual state licensing boards. Therefore, the 2015 American Community Survey is the source for much of the workforce supply data used for the LTSS workforce analysis (Exhibit 7).

The main strengths of the ACS are the availability of occupation code and industry code identifying LTSS setting; data are collected by the U.S. Census Bureau for a large sample of the population in each state; data are collected annually; and there is a wealth of information collected on labor force participation, hours worked, and characteristics of workers—including demographics and education level. There are, however, limitations with ACS to analyze the LTSS workforce:

- Nurse aides, home health aides and psychiatric aides are aggregated in the ACS data into one occupation comprising all aides. Therefore, we supplemented the ACS data with Bureau of Labor Statistics Occupational Employment Statistics (OES) data to estimate the portion of aides that were nurse aides, home health aides, and psychiatric aides (Exhibit 8). However, for modeling we categorize all home health aides under the home health setting.
- Some occupation-industry combinations reported in ACS can be unclear. For example, a home health agency owned by a hospital might be categorized under "hospital" for industry.

Exhibit 7: FTE LTSS Workforce, 2015 American Community Survey

Occupation	Long Term Care Settings				All Health Care Settings
	Total LTC	Nursing Facilities	Residential Care	Home Health	
Direct Care Workers	2,305,300	590,800	543,300	1,171,200	3,207,900
Nursing/Home Health/Psychiatric Aides	1,277,000	523,700	352,800	400,500	1,935,000
Nursing Assistants/Aides	742,500	523,500	159,000	60,000	Unavailable
Home Health Aides	522,700	<100	182,200	340,500	Unavailable
Psychiatric Aides	11,800	200	11,600	<100	Unavailable
Personal Care Aides	1,028,300	67,100	190,500	770,700	1,272,900
Registered Nurses	434,500	250,500	27,000	157,000	2,947,200
Licensed Practical and Licensed Vocational Nurses	361,700	219,400	35,300	107,000	801,000

Source: 2015 American Community Survey. Notes: Estimates of full time equivalents were calculated by dividing each person's reported weekly hours worked by 40 hours. ACS combines nursing aides, home health aides and psychiatric aides into one labor category. For this analysis, we divided these workers into their own occupations using the workforce distribution from the Occupational Employment Statistics (Exhibit 8) but categorizing all home health aides under the home health setting.

Exhibit 8: LTSS Workforce Jobs, 2015 Occupational Employment Statistics

Occupation	Long Term Care Settings				All Health Care Settings
	Total LTC	Nursing Facilities	Residential Care	Home Health	
Nursing Assistants/Aides	868,300	612,120	185,970	70,210	1,313,690
Home Health Aides	611,130	25,370	200,320	385,440	783,640
Psychiatric Aides	13,760	240	13,520	-	49,440

Source: *2015 Occupational Employment Statistics*. Note: Estimates based on employer surveys and counts do not distinguish between full time and part time staff. http://www.bls.gov/oes/current/oes311011.htm. Adult day care is not an industry category in OES.

Supply modeling for several occupations that work in LTSS settings is described elsewhere in this report—including RNs and LPNs (discussed in Chapter IV.B); behavioral health providers (discussed in Chapter IV.C); and physicians, APNs and PAs (discussed in Chapter IV.D).

While demand for these occupations is modeled by care delivery setting, supply is not. However, to the extent that comparisons of supply and demand for these occupations helps inform overall adequacy of future supply, one can draw conclusions about the implications for LTSS (which tends to pay lower compensation relative to acute care settings that might employ these health professionals). If the overall supply of nurses is projected to be more than adequate to meet demand for services across the health care sector, then within a particular employment sector (such as nursing homes) there is a greater likelihood that supply will be adequate (as compared to a situation where there were projections of a system-wide occupation shortage).

Modeling the supply of direct care workers in LTSS entails similar challenges to modeling demand. These include predicting how health care delivery may change over time; determining how a greater focus on team-based care may alter staffing levels; and estimating how improvements in technology may change staff loads. Additional challenges specific to modeling LTSS workforce supply relate to deriving setting-specific estimates, recognizing that many direct care workers may have a choice of workplace opportunities. Setting-specific workforce supplies are likely dependent on a number of factors, including wage competitiveness, employment benefits, workplace environment, and workplace recognition. These factors are especially important in understanding the dynamics and fluidity in workforce occupations where little or no specialized training is required. Estimating the relationships among these various drivers over time is beyond the scope of the current HWSM, although future versions of the model may be able to address these elements and thus allow estimation of health workforce supplies in specific care settings, including LTSS.

Still, analysis of ACS provides some insights on the potential future size of aide supply. Direct care workers are disproportionately female and minority (Exhibit 9). There are an estimated 2.6 million individuals working as a direct care worker in a LTSS role, equivalent to approximately

2.3 million FTEs (reflecting that some work part time). Together these FTEs represent 1.4% of the employed workforce in the U.S. in 2015. Only 0.2% of employed white, non-Hispanic males worked as a LTSS direct care worker, while 6.2% of black females worked as a direct care worker.

Exhibit 9: Aide Employment by Race-ethnicity and Sex, 2015

	Employed Aides	Total National Employed	Percent of Employed who are Aides
Female	**2,015,100**	**75,428,000**	**2.7%**
White, non-Hispanic	882,400	48,195,000	1.8%
Black, non-Hispanic	621,100	9,942,000	6.2%
Other, non-Hispanic	163,600	6,096,000	2.7%
Hispanic	348,000	11,195,000	3.1%
Male	**290,200**	**84,398,000**	**0.3%**
White, non-Hispanic	126,500	54,656,000	0.2%
Black, non-Hispanic	83,400	8,656,000	1.0%
Other, non-Hispanic	39,300	6,504,000	0.6%
Hispanic	41,000	14,582,000	0.3%
Total	**2,305,300**	**159,826,000**	**1.4%**

Source: 2015 American Community Survey. The "Other" category combines all remaining racial or ethnic groups which are not modeled separately due to small sample size in many of the databases analyzed (e.g., the Medical Expenditure Panel Survey for analyzing health care use patterns). This category includes Native Americans, Alaska Natives, Native Hawaiians and other Pacific Islanders, Asian Americans, Middle Easterners and North Africans, and others who self-identify as other than White, Black, or Hispanic.

Based on national changing demographics, populations with greater propensity to be direct care workers (Hispanics, blacks) are growing more rapidly than populations with lower propensity to be direct care workers (non-Hispanic white and other races).

2. Developing LTSS Workforce Demand Projections

The projected demand for LTSS and workforce was derived from the common model estimated on the baseline population and health care usage as outlined in Chapter III. HWSM already models the demand of many occupations relevant to LTSS (e.g., RNs, LPNs, nurse and home health aides), and these projections have been refined for modeling LTSS settings. Previous efforts to model LTSS settings used simplifying assumptions—such as modeling growth in demand for nursing homes and residential care services strictly as a function of an aging population (specifically, the population age 75 and older). Areas of enhancement to demand modeling include refining the relationship between patient characteristics and economic factors and use of LTSS services, adding the adult day care setting, including estimates for unpaid care demand, adding occupations to the model, and refining the scenarios modeled (taking into account possible changes in care use and delivery patterns).

The population file used for modeling demand was updated to include representative samples of the community-based, residential care-based and nursing home-based populations as noted in Chapter III. To construct the population file, historically a matching algorithm was used to combine the latest data from ACS, BRFSS, and NNHS. Starting with this analysis of the LTSS workforce, a representative sample of the population residing in a residential care facility was added (whereas previously this population was modeled as living in the community). We identified beneficiaries in the MCBS who reside in a residential care facility and used this sample to construct a representative sample of the population in each state living in residential care. Likewise, we used CMS's 2015 NHMDS to develop a representative sample of the population in nursing homes. The result was a population file with a representative sample of the population in each state who might use community based services including home health and adult day services, a representative sample of the population living in residential care facilities, and a representative sample for the population in a nursing home.

Baseline demand for LTSS was projected under the assumption that recent patterns of care use and delivery would remain unchanged within each demographic group defined by age, sex, and race-ethnicity. Predicted probabilities were applied to the simulated micro-data set for future years to obtain projected service use specific to the settings that employ long-term care occupations.

For modeling demand for adult day service centers, probabilities were assigned to specific population cohorts defined by age group and these probabilities were applied to the population database. The target population was identified as people living in communities with any cognitive difficulty. The probabilities based on age-distribution of adult day service center patients were obtained from the National Study of Long-Term Care Providers.[16] Approximately 4,800 adult day service centers reported employing around 23,100 FTE nurses and social workers.[17] Among the workforce modeled for the LTSS projections include an estimated 13,700 nurse aides, 4,100 RNs, and 2,500 LPNs working in adult day service centers.

HWSM used provider staffing patterns to convert demand for LTSS into demand for the relevant occupations. These staffing patterns were applied to the constructed population database to generate baseline state and national projections by LTSS setting and occupation. To construct the staffing ratios for home health, nursing homes and residential care facilities (Exhibit 10), we

[16] National Center for Health Statistics. Long-Term Care Services in the United States: 2013 Overview. December 2013. U.S. Department of Health and Human Services. Available at: http://www.cdc.gov/nchs/data/nsltcp/long_term_care_services_2013.pdf

[17] National Center for Health Statistics. Long-Term Care Providers and Services Users in the United States: Data from the National Study of Long-Term Care Providers, 2013 – 2014. February 2016. Appendix B Table 2. Available at: http://www.cdc.gov/nchs/data/nsltcp/2014_nsltcp_state_tables.pdf .

divided the workload driver, including number of home health visits and population size for age 75 and above, for each setting by estimates of FTE providers (Exhibit 7) from the 2015 ACS.

Exhibit 10: Ratio of Annual Care Utilization to FTEs, 2015

Occupation	Home Health	Nursing Home	Residential Care	Adult Day Service Centers
Personal Care Aides	29*	20	3.6	NA
Nursing Aide	371*	2.5	4.4	21
Home Health Aide	65*	NA	3.8	NA
Psychiatric Aide	NA	6,391	60	NA
Registered Nurses	142*	5.2	26	69
Licensed Practical and Licensed Vocational Nurses	208*	6.0	20	113

Note: Annual home health visits varies by occupation. * indicates staffing ratio is based on home health visits specific to the occupation as calculated using MEPS; all other occupations use ratios based on total annual home health visits (regardless of type of visit). NA indicates occupation is not applicable to the employment setting.

In addition to developing prediction equations for paid care, we analyzed NHATS to develop prediction equations of how much unpaid care is provided (i.e., informal care giver such as a family member or friend). The purpose of this analysis was to determine if trends affecting future supply and demand for unpaid care might affect future demand for paid care—and in particular future demand for direct care workers. The regression estimates from NHATS were applied to the non-nursing home population age 65 and older in the population database to model total hours of unpaid care.

First, using logistic regression we analyzed the propensity of individuals to use paid and unpaid care (Exhibit 11). Older age and presence of activities of daily living limitations were associated with greater odds of receiving both paid and unpaid care.

Second, using a negative binomial regression model we analyzed total paid and unpaid care hours received per week for those individuals who reported receiving at least one hour of care (Exhibit 12). FTE demand for unpaid care assumed 1 FTE equal to 40 hours of unpaid care. Older age and presence of select ADL limitations were associated with greater number of paid and unpaid hours per week of care received.

Exhibit 11: Whether a Person Uses Paid and Unpaid Care

	Characteristic	Use of Paid Care (Odds Ratios)	Use of Unpaid Care (Odds Ratios)
Race-Ethnicity	Non-Hispanic white	1.00	1.00
	Non-Hispanic black	1.19	1.17*

	Non-Hispanic other race	0.55**	0.86
	Hispanic	1.69**	1.16
	Male	1.07	1.51**
Age	65-69 years	1.00	1.00
	70-74 years	0.89	0.70**
	75-79 years	0.71**	0.93
	80-84 years	1.19	0.98
	85-89 years	1.41**	1.24**
	90+ years	1.63**	1.46**
Difficulty/Health Indicators	History of heart attack	1.17	0.94
	History of stroke	1.16	1.00
	Hearing difficulty	1.07	1.02
	Vision difficulty	1.49**	1.03
	Walking difficulty	2.24**	1.30**
	Self-care difficulty	4.83**	1.67**

Note: Logistic regression modeling use of paid care (yes/no) and unpaid care (yes/no). Statistically significant at the 0.01 (**) or 0.05 (*) level. n = 7,385.

Exhibit 12: Weekly Hours of Paid and Unpaid Care Received

	Characteristic	Paid Hours/Week (Rate Ratio)	Unpaid Hours/Week (Rate Ratio)
Race-Ethnicity	Non-Hispanic white	1.00	1.00
	Non-Hispanic black	1.08	1.64**
	Non-Hispanic other race	1.65*	1.59**
	Hispanic	1.37	1.43**
	Male	0.97	1.49**
Age	65-69 years	1.00	1.00
	70-74 years	1.01	0.80
	75-79 years	1.20	1.10
	80-84 years	1.30	1.09
	85-89 years	1.62*	1.31*
	90+ years	1.86**	1.12
Difficulty/Health Indicators	History of heart attack	0.91	0.95
	History of stroke	1.11	1.43**
	Hearing difficulty	1.03	1.06
	Vision difficulty	0.88	1.20
	Walking difficulty	1.74**	1.66**

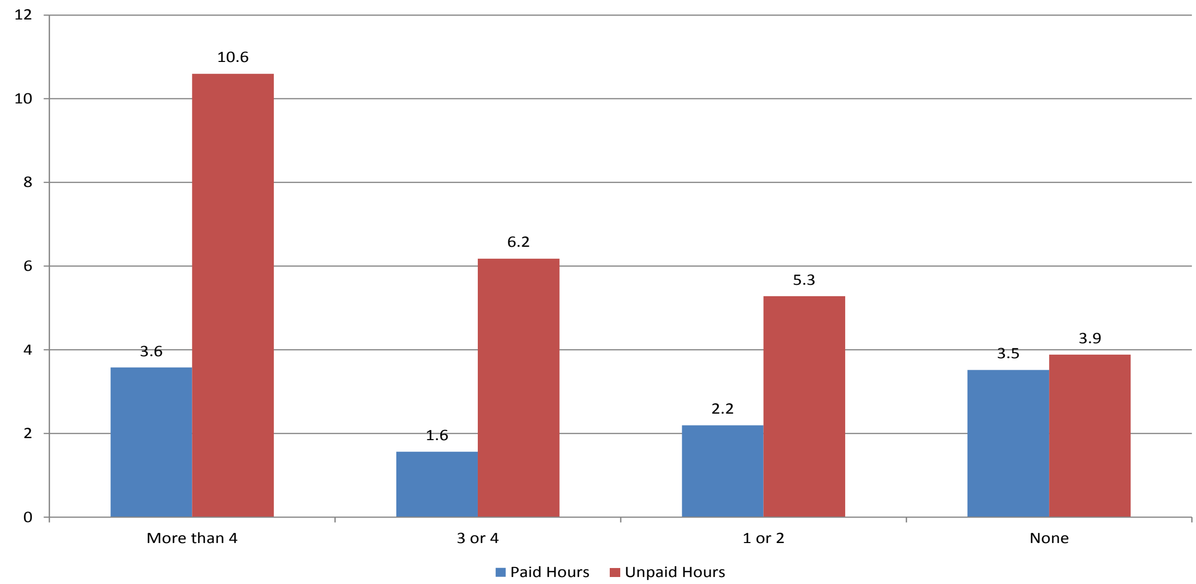
	Self-care difficulty	1.66**	1.30**

Note: Negative binomial regression modeling weekly hours of paid care and unpaid care. Statistically significant at the 0.01 (**) or 0.05 (*) level. n = 509 for paid care; n=1,242 for unpaid care.

The focus of this work was modeling growth in demand for unpaid hours of care, though projections of growth in paid hours of care were consistent with projected growth in demand for personal care aides and home health aides. We explored whether the trend to decreasing family size might affect future supply of unpaid care and the implications for demand for paid care.[18] Analysis of NHATS found that the smaller family size is correlated with greater weekly hours of paid care and fewer weekly hours of unpaid care. However, the overall impact of decreasing family size is relatively small and does not appear to substantially affect demand for paid care workers.

[18] Johnson RW, Toohey D, Weiner JM. Meeting the Long-Term Care Needs of the Baby Boomers: How Changing Families Will Affect Paid Helpers and Institutions. Retrieved from http://www.urban.org/research/publication/meeting-long-term-care-needs-baby-boomers.

Exhibit 13: Average Weekly Hours of Paid and Unpaid Care, by Number of Children



3. Baseline and Alternative LTSS Workforce Projections

The Baseline scenario for modeling demand assumes prevalence rates of functional impairments among people of different age, gender and race/ethnicity will remain constant over time. It assumes that recent patterns of care use and delivery will remain unchanged, but takes into account population growth and aging. Demand projections were developed at the state level and then aggregated to obtain the national projections. The state-level projections take into consideration geographic variation in health risk factors and demographics.

Demand also was modeled under a scenario focusing on forecasting population health status and to capture trends and expectations in care use and delivery. This Population Health scenario is described in more detail in Section IV. B, but assumes that the nation achieves sustained reductions in excess body weight; smoking cessation; and improving uncontrolled hypertension, hypercholesterolemia, and hemoglobin A1C levels. Such a scenario might be achieved under a medical home model, and is based on national priorities to improve access to preventive care. Trends that might help achieve such a scenario include: (a) increased organizational and policy commitment to population health as illustrated by health care reform, ACO-related quality metrics targeted at population health, and payment reform; (b) greater assumption of risk by providers (e.g., from bundled payments); and (c) better infrastructure to manage population health.

B. The Nursing Model (updated 2016)

1. Estimating Base Year Nurse Supply

For most states, estimates of the current supply of RNs and LPNs came from the pooled 2010-2014 ACS files. Five years of data were combined to increase the sample size to provide stable state-level estimates of the distribution of nurses by education level, age, sex and race/ethnicity (which is a new component added to the supply model). The ACS sample weights from the 5-year file were recalibrated to sum to the state totals of RNs and LPNs in the 2014 ACS. HWSM was designed to use data from state licensure files as data becomes available for use instead of ACS data.

Four states (Georgia, Oregon, South Carolina, and Texas) provided licensure data so for those states the starting supply is based on licensure data instead of the ACS.[19] Criteria for including nurses in the licensure files are that the nurse was licensed and active in nursing in the state being modeled. The main difference between the licensure files and ACS in terms of defining an active nurse is that with licensure files we could verify the nurse was licensed in the state, whereas with the ACS data licensure was implied by the ACS respondent self-reporting activity status and occupation as a nurse.

The ACS estimates extrapolated to 2015 averaged 5-8% higher for RNs-LPNs compared to estimates from the 2015 licensure files, though the differences varied by state-occupation combinations.[20] A comparison of ACS and licensure files for these four states suggests that (1) the RN estimates from the ACS appear to be more consistent with licensure files than are the LPN estimates from ACS—likely reflecting that LPN sample size is smaller in ACS compared to

[19] These state licensure data were 2015 data, while the ACS data was 2014 data. Consequently, to obtain 2014 estimates for these states we projected backwards based on projected graduates and attrition from 2014 to 2015.

[20] For example, ACS estimates for RNs in Georgia and South Carolina appear to be similar to estimates from state licensure files, while for Oregon the ACS estimate is smaller and for Texas the ACS estimate is larger. For LPNs, the Georgia and Texas estimates are relatively consistent with estimates from state licensure files, while for Oregon and South Carolina the ACS estimates are much larger in percentage terms than are estimates from state licensure files.

Source	GA	OR	SC	TX	4-State Total
RNs: 2015 projected from 2014 ACS	85,600	33,700	47,900	222,300	389,400
RNs: 2015 Licensure files	84,600	37,600	49,400	200,700	372,200
Difference (ACS-Licensure)	1,000	(3,900)	(1,500)	21,600	17,200
% Difference	1%	-10%	-3%	11%	5%
LPNs: 2015 projected from 2014 ACS	29,800	4,400	12,900	78,200	125,400
LPNs: 2015 Licensure files	27,900	3,400	8,600	76,500	116,400
Difference (ACS-Licensure)	1,900	1,000	4,300	1,700	9,000
% Difference	7%	29%	50%	2%	8%

sample size for RNs; (2) if at the national level ACS overestimates FTE supply of nurses then the estimates of national demand based on ACS also might be overestimated by a similar percentage; and (3) information from additional states would help determine to what extent the ACS accurately reflects estimates of supply from state licensure files.

2. Modeling New Entrants to the Nursing Workforce

New entrants reflect nurses entering the workforce for the first time upon completion of a nursing program, as well as individuals who migrate mid-career from one geographic area to another (discussed later). HWSM used first time, U.S.-educated candidates taking the National Council Licensure Examination (NCLEX) as the starting point for estimating the number of new entrants to the nursing workforce. In 2014, there were 157,882 first-time U.S.-educated takers of the NCLEX-RN.[21] Of these, 70,857 nurses had completed a baccalaureate degree and 87,025 had completed a diploma or an associate degree.[22] There were 55,489 first time takers of NCLEX-LPN in 2014. Based on the assumption that nurses who initially fail the NCLEX will retake the test at least twice, we assumed an eventual pass rate of 96% of RNs trained at the associate level, 98% of RN trained at the baccalaureate level, and 95% of LPNs, and that these nurses will enter the workforce.

For modeling future supply under a status quo scenario, HWSM assumed that annually the number of nurses passing the NCLEX includes 69,440 RNs at the baccalaureate level, 83,540 RNs at the associate or diploma level, and 52,720 LPNs. The new entrant statistics for RNs include the estimated 16,000 LPNs who further their education and become RNs each year. Alternative supply scenarios modeled include training 10% more or 10% fewer nurses, relative to current numbers, to illustrate the sensitivity of supply projections to the number of nurses being educated each year.[23]

The National League of Nursing survey of students enrolled in entry level nursing programs in 2014 suggests that 91% of LPNs are female, 86% of RNs in associate or diploma programs are female, and 85% of RNs in baccalaureate programs are female.[24] Estimates of the age distribution for new nurses come from analysis of the 2008 National Sample Survey of Registered Nurses (Exhibit 14). Limited data is available on the age distribution of new LPNs, but National League for Nursing data from 2008-2009 suggests that the age distribution for

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[21] Foreign educated NCLEX takers are excluded from this analysis because there is no evidence that employers currently are relying on foreign educated nurses to fill nursing vacancies. Many foreign educated nurses take NCLEX but do not come to the U.S.

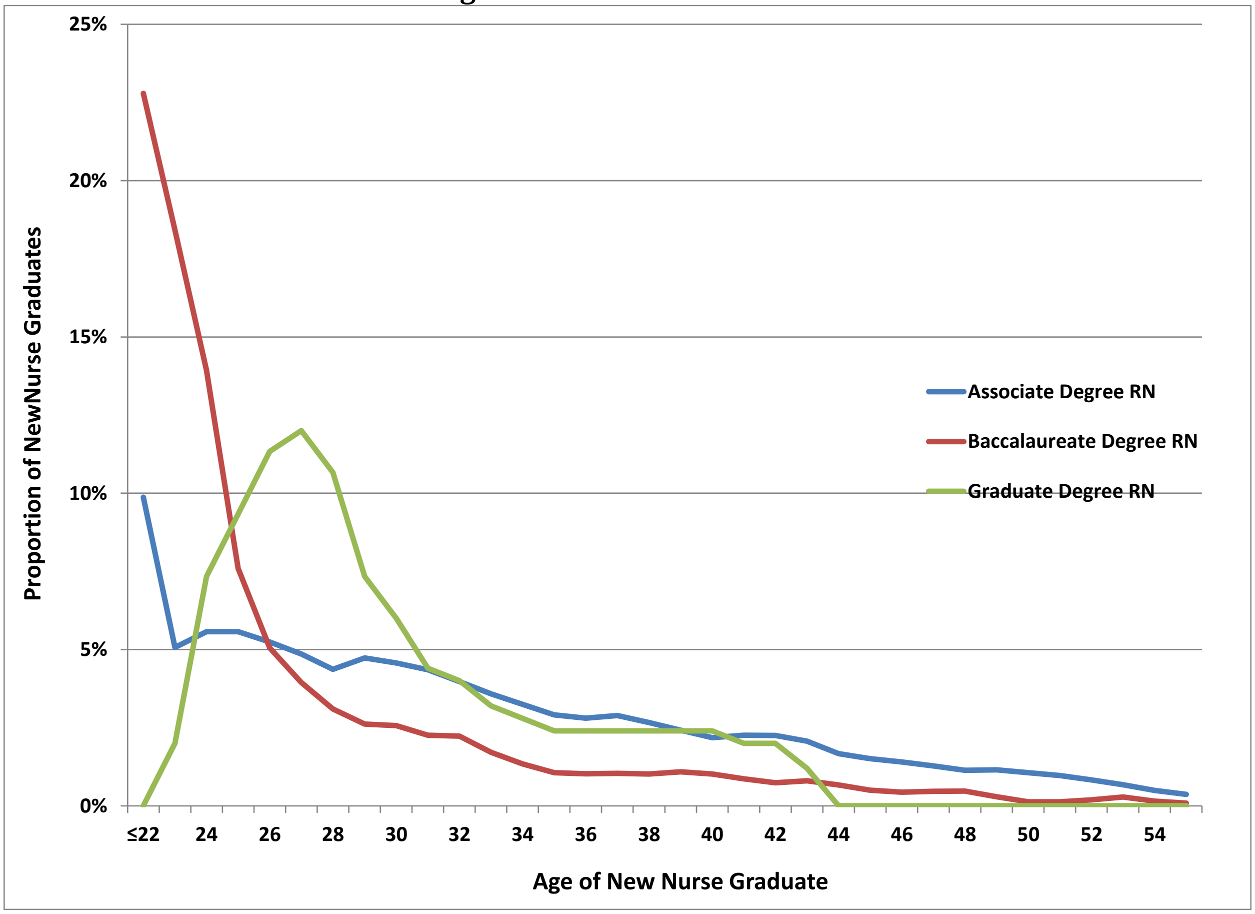
[22] National Council of State Boards of Nursing, Inc. *2014 Nurse Licensee Volume and NCLEX® Examination Statistics.* pg. 17 available athttps://www.ncsbn.org/15_2014_NCLEXExamStats_vol64.pdf.

[23] Additional scenarios modeled include ±5% change in nurse productivity levels, and ±2 years earlier or delayed retirement.

[24] National League for Nursing. Biennial Survey of Schools of Nursing, 2014. http://www.nln.org/researchgrants/slides/topic_nursing_stud_demographics.htm

LPNs is similar to the age distributions for Diploma and Associated Degree RNs.[25] Hence, for modeling we use the age distribution of Diploma and Associated Degree RNs as a proxy for the age distribution of LPNs. The race and ethnic distribution of new nurses varies widely by state, and we use the race/ethnicity distribution of nurses age 30 or younger in the 2010-2014 ACS as a proxy for the age distribution of new nurses (Exhibit 15).

Exhibit 14: Age Distribution of New RNs and LPNs



[25] National League for Nursing. Biennial Survey of Schools of Nursing, 2008-2009. http://www.nln.org/researchgrants/slides/topic_nursing_stud_demographics.htmhttp://www.nln.org/docs/default-source/newsroom/nursing-education-statistics/AS0809_F17.pdf-pdf.pdf

Exhibit 15: Race and Ethnicity Distribution of New RNs and LPNs by State

	Registered Nurses				Licensed Practical Nurses			
	Non-Hispanic				Non-Hispanic			
State	WHITE	BLACK	OTHER[a]	HISPANIC	WHITE	BLACK	OTHER[a]	HISPANIC
AK	95%	0%	5%	0%	71%	0%	29%	0%
AL	85%	11%	2%	3%	64%	33%	3%	0%
AR	83%	12%	1%	4%	70%	20%	7%	3%
AZ	70%	3%	9%	18%	59%	4%	12%	26%
CA	38%	3%	39%	21%	23%	9%	34%	34%
CO	83%	2%	6%	9%	52%	13%	6%	28%
CT	75%	11%	7%	6%	51%	26%	8%	14%
DC	56%	24%	10%	11%	17%	83%	0%	0%
DE	74%	19%	3%	4%	63%	29%	8%	0%
FL	53%	18%	10%	19%	43%	31%	5%	21%
GA	68%	23%	5%	4%	50%	45%	2%	3%
HI	29%	4%	59%	8%	41%	0%	49%	10%
IA	97%	1%	0%	2%	90%	6%	2%	2%
ID	94%	0%	2%	4%	89%	0%	0%	11%
IL	73%	5%	14%	8%	49%	28%	12%	11%
IN	90%	4%	3%	3%	76%	14%	2%	8%
KS	86%	7%	4%	4%	71%	9%	9%	12%
KY	92%	5%	2%	0%	86%	11%	3%	0%
LA	71%	22%	3%	3%	52%	44%	2%	2%
MA	78%	8%	9%	5%	70%	15%	7%	9%
MD	58%	23%	14%	5%	46%	47%	2%	4%
ME	98%	0%	2%	0%	98%	0%	2%	0%
MI	89%	5%	4%	2%	65%	29%	4%	2%
MN	89%	4%	4%	2%	81%	9%	8%	3%
MO	87%	9%	3%	2%	71%	23%	3%	2%
MS	76%	22%	1%	1%	47%	46%	4%	4%
MT	97%	0%	3%	0%	83%	0%	17%	0%
NC	83%	11%	4%	3%	68%	23%	5%	3%
ND	92%	2%	5%	1%	70%	0%	30%	0%
NE	92%	3%	2%	3%	90%	4%	3%	4%
NH	92%	4%	3%	0%	73%	3%	14%	9%
NJ	59%	12%	19%	10%	37%	39%	11%	14%
NM	49%	1%	5%	45%	21%	2%	21%	56%
NV	47%	9%	37%	7%	64%	3%	16%	16%
NY	59%	18%	15%	8%	52%	33%	5%	10%
OH	90%	7%	2%	2%	68%	28%	1%	3%
OK	74%	8%	14%	4%	62%	15%	21%	3%
OR	85%	0%	10%	5%	65%	0%	24%	11%
PA	87%	6%	4%	2%	74%	18%	3%	5%
RI	81%	3%	14%	1%	43%	10%	13%	34%
SC	73%	20%	6%	2%	63%	35%	1%	1%
SD	95%	1%	4%	0%	98%	0%	0%	2%
TN	87%	9%	2%	2%	82%	13%	2%	3%
TX	56%	11%	11%	22%	42%	16%	5%	37%
UT	93%	1%	4%	2%	91%	0%	5%	5%
VA	75%	13%	8%	4%	52%	35%	6%	7%
VT	100%	0%	0%	0%	88%	0%	10%	2%
WA	75%	5%	16%	4%	70%	2%	17%	11%
WI	91%	2%	4%	3%	86%	6%	4%	4%
WV	96%	1%	2%	0%	96%	4%	0%	0%
WY	95%	0%	1%	4%	82%	0%	7%	12%
US	73%	9%	10%	8%	57%	21%	9%	13%

Notes: Analysis of race and ethnic identify of nurses age 30 or under in the 2010-2014 combined files of the American Community Survey. [a] "Other" category includes Asian and Pacific Islander and American Indian.

3. Modeling Nurse Workforce Participation

Nurses might temporarily leave the labor force due to family, education, economic or other considerations. Permanent departure from the labor force might be due to retirement, career change to another occupation, or death—or when modeling workforce for a particular geographic area might be the result of emigration (moving away from that geographic location to work elsewhere). This section describes permanent attrition from the workforce modeling, labor force participation, and weekly hours worked. Modeled hourly wage—which is one input used to model labor force participation and hours worked patterns—also is described.

a) Attrition Patterns

In this section we describe analyses and assumptions regarding nurses who permanently leave the nursing workforce—which differs from temporary departures such as for child rearing, illness, or other reasons where the nurse intends to eventually return to employment.

We modeled a small amount of attrition each year for nurses under age 50. The preliminary RN supply projections assumed that about 97% of RNs taking the NCLEX exam for the first time would eventually pass and enter the workforce. We then modeled labor force participation rates using the ACS, and estimated that about 92-95% of RNs would be active in the workforce through age 50 depending on age. After age 50 we model attrition from the workforce as nurses age.

The challenge with ACS data is that if an RN has been out of the workforce for five or more years then ACS does not collect occupation data. However, if the RN remains in the workforce but in a non-nursing position then their occupation will not indicate RN but indicate the current occupation. While our starting supply of RNs will be accurate, our labor force participation rates will not reflect some younger RNs permanently leaving nursing.

HRSA's 2008 Sample Survey of RNs indicates that a small percentage of RNs under age 50 intends to leave the workforce, and a small percentage of recent graduates are not employed in nursing.[26] However, this snapshot for 2008 was in the middle of a national recession. Also, of nurses not working in nursing many plan to return to nursing. One challenge with the survey data is that when a nurse indicates an intention to leave nursing in the next 3 years (i.e., the question asked) it is unclear whether the intention is to permanently or temporarily leave nursing. The survey indicates that for nurses under age 50 who are not working in nursing approximately

[26] U.S. Department of Health and Human Services, Health Resources and Services Administration (2010). The Registered Nurse Population: Findings from the 2008. National Sample Survey of Registered Nurses. See Figure 3-4, Figure 3-24, Table 6-1 and Table 9-14. Access at: https://bhw.hrsa.gov/sites/default/files/bhw/nchwa/rnsurveyfinal.pdf

57.5% have been out of nursing for 0-4 years (so presumably most of these nurses are represented in the ACS unless they are working in a different occupation so their occupation code changed). An estimated 42.5% of nurses who have left nursing have been out of nursing for five or more years so these nurses would not be represented in ACS as a nurse. Therefore, the ACS likely understates the number of trained nurses who are not active in nursing by a few percentage points. Some nurses who indicate they are not in nursing are in other health occupation or government jobs, so it is possible that these nurses still are working in a role that requires a nursing background or degree even though the nurse is not practicing in a traditional nursing role.

According to the 2008 survey[26], by age 30-34 approximately 8.7% of nurses are not employed in nursing, growing to about 10% from age 40-49. Analysis of the ACS indicates about 92-95% not employed in nursing (with the percentage not employed varying by age). Based on the data in Figure 3-4 and Figure 3-24 of the 2008 survey report we make the following assumptions:

1. From when the nurse initially enters the workforce through age 39 each year there is a 0.33% probability of leaving the workforce each year. For example, if a nurse enters the workforce at age 25 then by age 39 she has a cumulative 3.3% probability of having permanently left nursing (on top of an approximately 5% probability of being out of the workforce).
2. Between age 40 and 49 there is an estimated 0.42% probability of leaving the workforce each year (based on our calculations). By age 49 a nurse who entered the workforce at age 25 has an 8.8% cumulative probability of having permanently left the workforce (on top of an approximately 5% probability of being inactive).

In summary, the modeling assumptions are that approximately 3% of nurses who graduate from a nursing program do not pass the NCLEX and enter the workforce; there is an 8.8% probability of leaving nursing by age 49 and a 92-95% employment rate for those in nursing through age 49; and from age 50 and older the nurses have a probability of permanently leaving the workforce that increases with age (as described later). For each 100 nurses graduated from a nursing program at age 25, we calculate by age 49 approximately 84 of these nurses would be working in nursing (with 3 never entering the workforce, 8 having left nursing altogether, and 5 currently out of the workforce).

Multiple approaches have been explored and used to estimate nurse retirement patterns. Prior to 2016, ACS-derived labor force participation rates by age and sex for RNs age 50 and younger were used. For RNs over age 50 labor force participation rates for college educated men and women over age 50 were used as a proxy for labor force participation rates for male and female

RNs over age 50 with a similar education level (i.e., with an associate degree, a baccalaureate degree, or a graduate degree). As noted above, ACS does not capture occupation for individuals out of the workforce for five years or more.

Refined estimates of nurse retirement patterns are used in the updated supply projections based on licensure data from Oregon, South Carolina and Texas (Exhibit 16). Multiple years of licensure data (2010-2015) were analyzed. These licensure data do not contain individual identifiers to link nurses across years. Therefore, we compared the age distribution of active RNs in one year to the expected age distribution in a subsequent year if all RNs active in prior year had remained active. The gap reflects net attrition from the workforce (including mortality, retirement and net migration out of the state).

The Oregon data reflected a survey question about intention to retire within the next three years. Based on informal communications with staff from the Oregon Center for Nursing, approximately a quarter of all nurses who in 2010 had expressed an intention to retire within the next three years were still in the workforce in 2014. Therefore, we adjusted the estimated attrition patterns based on intention to retire to reflect Oregon's previous analysis that intention to retire might overstate actual retirement. Also, we added mortality patterns to the intention to retire patterns to estimate overall attrition rates.

The supply projections are based on the average retirement patterns estimated across the three states. Retirement patterns differ by age and nurse type (RN or LPN), but do not differ by other nurse characteristics. This is an area of ongoing research. Also, the retirement patterns used in the model reflect input from participants in a recent nurse workforce retreat sponsored by HRSA.[27]

For nurses age 70 and older the sample sizes in the state licensure files are small and estimates of retirement patterns fluctuate accordingly. Therefore, we assume that starting at age 70 the annual attrition rate is 50%. In addition, we model that annually approximately 16,000 LPNs become RNs and approximately 16,200 RNs leave the RN workforce each year to become nurse practitioners (reflecting that close to 15% of NPs remain practicing in a traditional RN role).

The approach used for modeling retirement patterns reflects limitations with data sources such as ACS. If a person has been out of the workforce for 5 years or more, then ACS does not collect information on prior occupation. Likewise, if a person left nursing for a career outside of nursing

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[27] In July 2016, HRSA and the Montana State University Center for Interdisciplinary Health Workforce Studies sponsored a 3-day meeting of nurse workforce researchers to critique alternative approaches to modeling nurse workforce supply and demand and to provide input on HRSA's workforce modeling assumptions, inputs and methods. One outcome of this meeting was to incorporate workforce attrition probabilities among younger nurses, and to adjust estimates of the number of RNs being trained as advanced practices nurses to reflect that some RNs become trained as APNs but still continue to practice in a traditional RN role.

then the ACS captures data on the current occupation but there is no indication of previously having been working in nursing. Hence, estimates of retirement patterns based on ACS can understate true retirement patterns.

Exhibit 16: RN Estimated Retirement Patterns

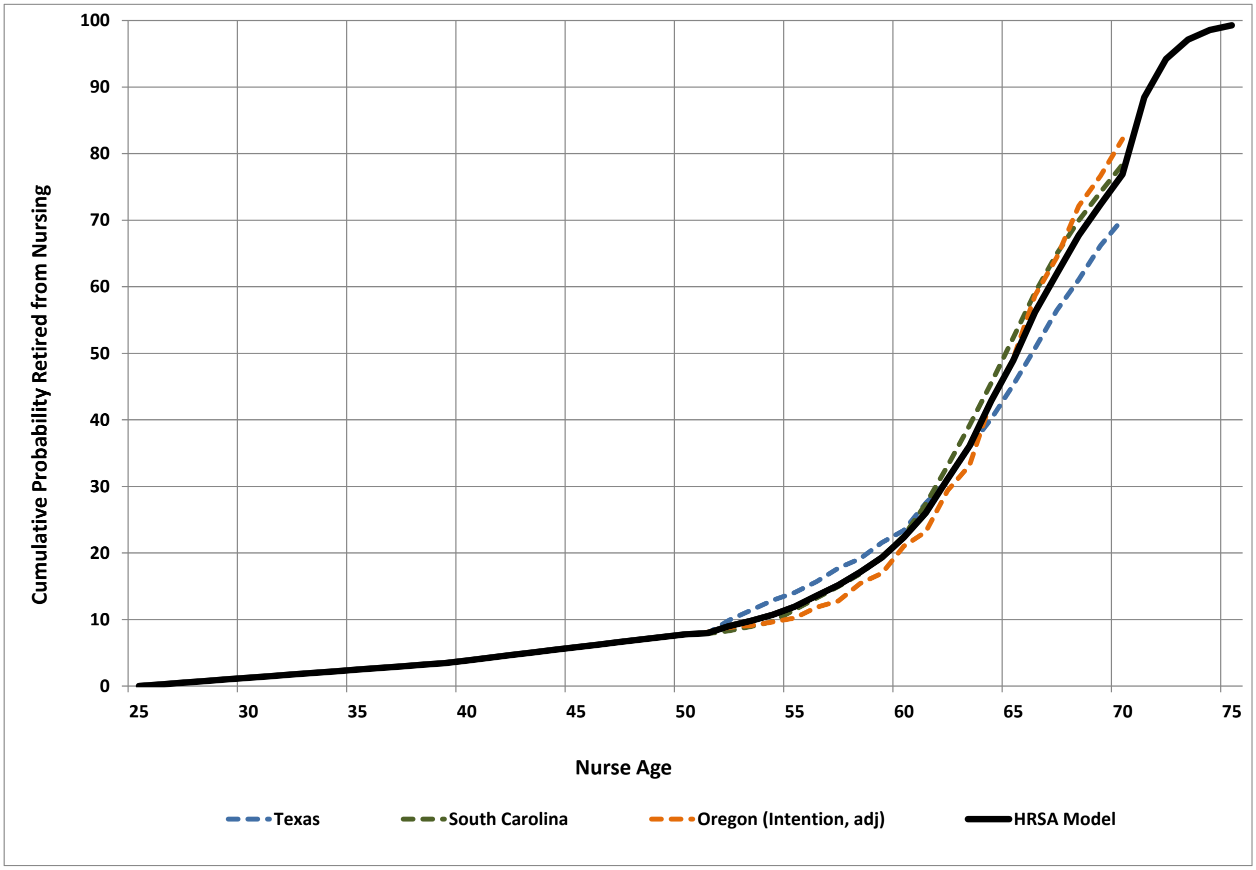

Exhibit 16: RN Estimated Retirement Patterns

b) Hourly Wages

Earnings potential (modeled in terms of hourly wages) are modeled as a function of nurse characteristics and external factors as summarized in Exhibit 17. The equations to predict hourly wages were estimated separately by nursing occupation using data from the 5-year (2010-2014) ACS for individuals who are currently employed. Hourly wages were calculated by dividing estimated weekly earnings by estimated weekly hours and omitting records where hourly wages were below the 5th percentile of above the 95th percentile (as estimated hourly wages for these omitted records were outside the plausible range). Included as an explanatory variable is state mean hourly wage for that occupation from the BLS Occupational Employment Statistics, with mean wage varying across states and years. Both occupation mean hourly wage and each person's hourly wage (i.e., the dependent variable in the regression) were adjusted to 2015 dollars using the consumer price index and adjusted to a national average using a state cost-of-living index.[28]

For the nursing occupations modeled, individual wage is highly correlated with occupation mean wage in that state. Wages tend to increase for those early in their career, but rise more slowly above age 35. Male nurses tend to earn higher hourly wages. Wages vary by race/ethnicity. Hourly wages rises with the percentage of the population living in suburban areas. As with many cross-sectional analyses using person-level data, the R-squared values for these equations are low reflecting that these regressions explain only a small portion of cross-sectional variation in hourly wages worked.

Exhibit 17: OLS Regression Coefficients Predicting RN/LPN Hourly Wages

Parameter	RN	LPN
Intercept	-2.67 **	-0.46
Unemployment rate (state, year) [a]	-0.15 **	-0.03
State occupation mean hourly wage [a]	0.85 **	0.84 **
Age 35 to 44 [b]	3.87 **	2.15 **
Age 45 to 54 [b]	5.21 **	2.80 **
Age 55 to 59 [b]	5.79 **	3.41 **
Age 60 to 64 [b]	5.74 **	3.43 **
Age 65 to 69 [b]	4.70 **	3.42 **
Age 70+ [b]	2.07 **	2.58 **
Male [b]	1.18 **	0.62 **
Year 2011 [b]	-0.38 **	-0.46 **
Year 2012 [b]	0.39 **	-0.44 **
Year 2013 [b]	0.14	-0.40
Year 2014 [b]	-0.29 **	-1.72 **
Non-Hispanic black [b]	-0.15	0.60 **
Non-Hispanic other [b]	-0.66 **	0.38 **
Hispanic [b]	1.12 **	-0.82 *
Have nursing baccalaureate degree [b]	2.55 **	NA
Having nursing graduate degree [b]	4.10 **	NA
Percentage of state's population residing in a suburban area	0.13 **	0.76 **
Percentage of state's population residing in a rural area	0.01	0.01 **
Sample size	150,504	37,294
R-square	0.12	0.11

[28] Missouri Economic Research and Information Center. https://www.missourieconomy.org/indicators/cost_of_living/

Notes: Statistically significant at the 0.01 (**) or 0.05 (*) level. [a] State mean by year from the Bureau of Labor Statistics. [b] Comparison groups are age <35, female, year=2010, non-Hispanic white, and (for RNs only) associate or diploma as highest educational degree. Source: Analysis of the 2010-2014 files of the American Community Survey.

c) Hours Worked

Forecasting equations related average hours worked to nurse age, sex, education level, state overall unemployment rate, and average wage in the occupation. Data for all variables came from the ACS with the exception of average wage, which was obtained from the BLS. To convert average hours worked into Full Time Equivalents (FTEs), an assumption needed to be made about the average number of hours worked per week by a full-time nurse. Analysis of the ACS suggests that among nurses working at least 20 hours per week, for both RNs and LPNs the average hours worked per week is 37.3. However, for modeling purposes HRSA is now defining an FTE as 40 hours per week (a measure which can remain constant over time and across health occupations). While workforce projections published before 2017 used different hour estimates to define an FTE, from 2017 onward the decision was to use 40 hours.

Ordinary Least Squares regression coefficients showed that average weekly hours worked declined substantially among older nurses (Exhibit 18). For both RNs and LPNs, weekly hours worked decline rapidly from age 60 onward. On average, male RNs work 2.78 more hours and male LPNs work 1.77 more hours than their female counterparts. Hispanic RNs work 2.28 hours more than non-Hispanic white RNs, RNs with a baccalaureate or graduate degree work 1.43 hours more than RNs with an associate or diploma degree, and RNs and LPNs in states with a larger proportion of the population residing in rural areas[29] tend to work more hours. Hours worked per week by RNs and LPNs rises slightly with the unemployment rate.

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[29] Metropolitan, suburban, and rural were defined using USDA's 2013 Urban Influence Codes (UIC) which are applied to each county. Metropolitan counties are UIC 1 and 2, we define suburban as codes 3 through 6, and define rural as codes 7 through 12.

Metropolitan	
1	In large metro area of 1+ million residents
2	In small metro area of less than 1 million residents
Suburban	
3	Micropolitan area adjacent to large metro area
4	Noncore adjacent to large metro area
5	Micropolitan area adjacent to small metro area
6	Noncore adjacent to small metro area and contains a town of at least 2,500 residents
Rural	
7	Noncore adjacent to small metro area and does not contain a town of at least 2,500 residents
8	Micropolitan area not adjacent to a metro area
9	Noncore adjacent to micro area and contains a town of at least 2,500 residents
10	Noncore adjacent to micro area and does not contain a town of at least 2,500 residents
11	Noncore not adjacent to metro or micro area and contains a town of at least 2,500 residents

Exhibit 18: OLS Regression Coefficients Predicting Weekly Hours Worked for RNs and LPNs

Parameter	Registered Nurses	Licensed Practical Nurses
Intercept	35.15 **	34.44 **
Unemployment rate (state, year) [a]	0.05 *	0.05
Predicted wage	0.01	0.04
Age 35 to 44 [b]	0.26 **	1.85 **
Age 45 to 54 [b]	1.20 **	2.04 **
Age 55 to 59 [b]	0.88 **	1.52 **
Age 60 to 64 [b]	-0.31 **	0.35
Age 65 to 69 [b]	-4.54 **	-4.33 **
Age 70+ [b]	-8.57 **	-7.42 **
Male [b]	2.78 **	1.77 **
Year 2011 [b]	0.14	-0.02
Year 2012 [b]	0.21 *	0.27
Year 2013 [b]	0.30 **	0.17
Year 2014 [b]	0.38 **	0.22
Non-Hispanic black [b]	-0.24 **	1.05 **
Non-Hispanic other [b]	1.56 **	1.16 **
Hispanic [b]	2.28 **	1.04 **
Have nursing baccalaureate degree [b]	1.43 **	NA
Having nursing graduate degree [b]	1.43 **	NA
State's percentage of population residing in a suburban area	0.73	-2.09 *
State's percentage of population residing in a rural area	1.41 **	1.96 **
Sample size	150,504	37,294
R-squared	0.04	0.04

Note: Statistically significant at the 0.01 (**) or 0.05 (*) level. [a] State mean by year from the Bureau of Labor Statistics. [b] Comparison groups are age <35, female, year=2010, non-Hispanic white, and (for RNs only) associate or diploma as highest educational degree. Odds ratios reflect 100% suburban versus 0%, or 100% rural versus 0%. Source: Analysis of the 2010-2014 files of the American Community Survey.

d) Activity Status

Activity status for nurses is modeled using prediction equations derived from ACS (2010-2014) data. This analysis focused on nurse clinicians under age 50 (as the activity status for clinicians

12 Noncore not adjacent to metro or micro area and does not contain a town of at least 2,500 residents

over age 50 is modeled as retirement). The dependent variable was whether the nurse was employed or not employed. The unemployed population is everyone currently not employed but whose most recent employment in the past five years was in nursing. Explanatory variables are the same used to model hours worked. The overall activity rate for RNs and LPNs under age 50 was, respectively 95% and 91%. The odds of being employed vary by nurse demographics—in particular age (Exhibit 19). A higher overall unemployment rate slightly raises the odds of RNs being employed, while higher earnings potential is associated with a slight decrease in the odds that RNs are employed. Interaction terms for gender and age group are included to reflect that labor force participation differences between men and women might differ by age group. To compare male RNs age 35-39 versus female RNs of the same age, one multiplies the odds ratios for male and the male-age interaction. For example, male RNs age 35-39 have twice the odds (0.71*2.81=2.00) of being active in the nursing workforce as do female RNs of the same age. Male RNs age 45-49 have odds of being active in the labor force that are 1.38 times the odds for female RNs of similar age.

Compared to non-Hispanic white nurses, the odds that an RN is active in nursing is 38% higher for Hispanics, 32% higher for non-Hispanic blacks, and 23% higher for non-Hispanic "other race" RNs. Non-Hispanic black LPNs have 42% higher odds of being active in nursing compared to non-Hispanic white LPNs.

Exhibit 19: Odds Ratios Predicting Probability RN/LPN Active

Parameter	RN Odds Ratio and 95% CI			LPN Odds Ratio and 95% CI		
Unemployment rate (state, year) [a]	1.03*	1.01	1.05	0.99	0.96	1.03
Predicted hourly wage	0.97*	0.96	0.99	1.01	0.99	1.04
Age 30-34	0.69*	0.63	0.77	1.00	0.87	1.16
Age 35-39	0.89	0.79	1.00	1.08	0.92	1.26
Age 40 to 44	0.97	0.86	1.08	1.10	0.94	1.29
Age 45 to 49	1.12	0.99	1.27	1.08	0.92	1.27
Male [b]	0.71*	0.58	0.87	1.39*	1.03	1.88
Interaction between age and gender						
Age 30-34 * male	2.20*	1.59	3.06	1.36	0.77	2.41
Age 35-39 * male	2.81*	1.96	4.02	1.06	0.62	1.81
Age 40 to 44 * male	2.63*	1.87	3.70	1.31	0.76	2.27
Age 45 to 49 * male	1.94*	1.38	2.74	0.79	0.48	1.29
Year 2011 [b]	0.93	0.84	1.03	0.89	0.76	1.04
Year 2012 [b]	0.92	0.83	1.02	0.87	0.74	1.02
Year 2013 [b]	0.93	0.84	1.05	0.91	0.76	1.08
Year 2014 [b]	0.97	0.85	1.10	0.80*	0.66	0.98
Non-Hispanic black [b]	1.32*	1.17	1.49	1.42*	1.24	1.62

Non-Hispanic other race [b]	1.23*	1.10	1.37	0.91	0.77	1.09
Hispanic [b]	1.38*	1.19	1.60	1.04	0.88	1.22
Have nursing baccalaureate degree [b]	0.98	0.91	1.05	NA		
Having nursing graduate degree [b]	0.91	0.80	1.03	NA		
State's percentage of population residing in a suburban area	2.27*	1.33	3.89	1.26	0.54	2.95
State's percentage of population residing in a rural area	0.77	0.52	1.15	0.47*	0.26	0.84
Sample size	89,370			23,348		

Notes: Odds ratios and 95% confidence interval (CI) from logistic regression. * Statistically different from 1.0 at the 95% level. [a] State mean by year from the Bureau of Labor Statistics. [b] Comparison groups are female, year=2010, non-Hispanic white, age <30. Labor force participation regression uses only clinicians under age 50. Source: Analysis of the 2010-2014 files of the American Community Survey.

4. Cross-state Migration Patterns

Previous nursing projections for HRSA modeled two migration scenarios: (1) newly trained nurses remain in the state in which they are trained; and (2) nurses completing training migrate across states based on the relative distribution of growth in employment opportunities. Under this second scenario, states with faster employment growth might experience a net inflow of nurses trained in other states with fewer employment opportunities.

For this update, we start with the assumption that nurses will initially enter the workforce in the state where they took the NCLEX exam. We then model cross-state migration based on prediction equations estimated using logistic regression on with the 5-year (2010-2014) ACS file. Cross-state migration was modeled in two steps: 1) modeling whether a person moves out of a particular state, and 2) modeling whether a person moves into a particular state. Of 134,593 RNs in the 5-year file (with different nurses surveyed each year), 2,526 (1.9%) indicated working in a different state compared to a year ago. Of the 34,555 LPNs in this file there were 495 (1.4%) who indicated working in a different state compared to a year ago.

Analysis of nurse cross-state migration patterns suggests that: 1) The probability of migration declines with age, with nurses age 30 and below having the highest probability of migrating to another state; 2) Male RNs are more likely to move than female RNs; 3) RNs whose predicted hourly wages (a continuous variable) exceeds the national average wage are less likely to migrate to another state; 4) RNs with higher levels of educational attainment (bachelors and graduate-level degrees) are more likely to move across state; and 5) White RNs are more likely to relocate compared to other race/ethnicity groups (Exhibit 20).

Exhibit 20: Logistic Regression for Probability of Nurses Moving Out of State

	Registered Nurses			Licensed Practical Nurses		
Parameter	**Odds Ratio**	**95% Confidence Interval**		**Odds Ratio**	**95% Confidence Interval**	
Unemployment rate	0.97*	0.94	0.99	0.96	0.90	1.03
Predicted hourly wage	0.97*	0.96	0.99	1.04	0.99	1.10
Age group [a]						
30-34	0.53*	0.47	0.60	0.56*	0.42	0.75
35-39	0.40*	0.35	0.47	0.44*	0.32	0.61
40-44	0.35*	0.30	0.40	0.40*	0.29	0.55
45-49	0.29*	0.25	0.34	0.31*	0.22	0.44
50-54	0.24*	0.20	0.29	0.29*	0.20	0.40
55-59	0.23*	0.19	0.27	0.20*	0.14	0.30
Male [b]	1.52*	1.35	1.72	1.44*	1.10	1.89
Year [c]						
2011	0.96	0.84	1.09	1.19	0.88	1.61
2012	0.90	0.79	1.03	0.96	0.69	1.33
2013	0.93	0.81	1.07	1.20	0.86	1.68
2014	0.94	0.80	1.10	1.22	0.84	1.77
Education level [d]						
Bachelors	1.60*	1.45	1.76	NA		
Graduates	2.24*	1.93	2.61	NA		
Race/ethnicity [e]						
Hispanic	0.80*	0.68	0.94	1.13	0.90	1.42
Non-Hispanic black	0.73*	0.63	0.85	0.87	0.60	1.27
Non-Hispanic other	0.86	0.71	1.03	0.68	0.46	1.00
State's percentage of population residing in a rural area	1.04*	1.02	1.06	1.06*	1.02	1.17
Unweighted sample	N=134,593			N=34,555		

Note: Comparison groups are: [a] under age 30, [b] female, [c] 2010, [d] associates degree for RNs (not applicable for LPNs), and [e] non-Hispanic white. Source: Analysis of the 2010-2014 files of the American Community Survey. * Statistically different from 1.0 at the 5 percent level.

Using the ACS sample weights this analysis from 2010-2014 suggests that annually approximately 59,802 RNs and 12,220 LPNs change states. When modeling cross-state migration patterns, HWSM uses the above equations to generate a probability that each nurse will migrate out of the state. This probability is then compared to a random number between 0 and 1 using a uniform distribution. If the random number is below the estimated probability of moving then the nurse is moved out of that state.

To ensure that the national number and characteristics of nursing moving out of states matches the number and characteristics of nurses moving into states, when a nurse is simulated to move out of state that nurse is reassigned to another state using the distributions in Exhibit 21. Between 2010 and 2014, of the estimated 59,802 RNs who move to another state each year approximately 1% moved to Alabama and 8.1% moved to California.

Over time, projections of number of nurses exiting a particular state changes based on the characteristics of nurses in that state and overall number of nurses. The variation across states and across years reflects both the modeling of migration determinants and use of a random number generator to allocate moving nurses across the various states based on the geographic distributions described previously. As illustrated in Exhibit 22, Alaska is projected to have a net import of 179 RNs per year and 51 LPNs per year (i.e., more nurses will move into the state each year than move out of the state).

Exhibit 21: State Distribution of Annual Nurse In-migration

	Registered Nurses		Licensed Practical Nurses	
	Annual Number	National Distribution	Annual Number	National Distribution
AK	444	0.7%	79	0.6%
AL	595	1.0%	202	1.7%
AR	571	1.0%	194	1.6%
AZ	2,280	3.8%	302	2.5%
CA	4,864	8.1%	397	3.2%
CO	2,123	3.6%	312	2.6%
CT	624	1.0%	114	0.9%
DC	289	0.5%	30	0.2%
DE	224	0.4%	84	0.7%
FL	4,472	7.5%	956	7.8%
GA	2,287	3.8%	534	4.4%
HI	626	1.1%	218	1.8%
IA	604	1.0%	70	0.6%
ID	407	0.7%	120	1.0%
IL	1,253	2.1%	514	4.2%
IN	734	1.2%	285	2.3%
KS	838	1.4%	138	1.1%
KY	852	1.4%	118	1.0%
LA	577	1.0%	191	1.6%
MA	1,191	2.0%	118	1.0%
MD	1,672	2.8%	199	1.6%
ME	520	0.9%	105	0.9%
MI	819	1.4%	203	1.7%
MN	920	1.5%	159	1.3%
MO	1,492	2.5%	214	1.8%
MS	556	0.9%	162	1.3%
MT	384	0.6%	77	0.6%
NC	2,872	4.8%	355	2.9%
ND	266	0.4%	169	1.4%
NE	432	0.7%	19	0.2%
NH	433	0.7%	90	0.7%
NJ	1,089	1.8%	219	1.8%
NM	872	1.5%	184	1.5%
NV	817	1.4%	126	1.0%
NY	1,608	2.7%	477	3.9%
OH	1,652	2.8%	347	2.8%
OK	521	0.9%	153	1.3%
OR	1,020	1.7%	30	0.2%
PA	1,921	3.2%	355	2.9%
RI	138	0.2%	67	0.6%
SC	1,157	1.9%	193	1.6%
SD	120	0.2%	41	0.3%
TN	1,503	2.5%	468	3.8%
TX	4,636	7.8%	1,584	13.0%
UT	477	0.8%	63	0.5%
VA	2,186	3.7%	504	4.1%
VT	256	0.4%	35	0.3%
WA	1,983	3.3%	217	1.8%
WI	934	1.6%	138	1.1%
WV	427	0.7%	262	2.1%
WY	264	0.4%	29	0.2%
U.S.	59,802	100%	12,220	100%

Source: Analysis of the 2010-2014 files of the American Community Survey.

Exhibit 22: RNs Average Annual Net Cross State Migration, 2015-2030

State	Average Annual Migration (Move-in Minus Move-Out)	Estimated 2015 FTE Supply	Projected 2030 FTE Supply
AK	179	16,400	18,400
AL	-920	68,000	85,100
AR	-242	28,400	42,100
AZ	1,185	65,700	99,900
CA	775	277,400	343,400
CO	1,291	41,900	72,500
CT	-14	34,000	43,500
DC	175	1,800	8,800
DE	80	9,600	14,000
FL	1,004	170,600	293,700
GA	893	77,200	98,800
HI	332	10,900	19,800
IA	-418	32,500	45,400
ID	139	11,200	18,900
IL	-1,135	116,300	143,000
IN	-834	62,900	89,300
KS	-61	29,500	47,500
KY	-510	44,900	64,200
LA	-330	40,600	52,000
MA	-364	73,200	91,300
MD	643	58,700	86,000
ME	205	14,600	21,200
MI	-1,076	91,600	110,500
MN	-353	56,200	71,800
MO	-120	59,600	89,900
MS	-349	29,100	42,500
MT	-18	9,600	12,300
NC	1,447	90,000	135,100
ND	-162	7,600	9,900
NE	-317	20,300	24,700
NH	111	15,500	21,300
NJ	-104	81,700	90,800
NM	520	15,900	31,300
NV	613	18,300	33,900
NY	-2,226	174,100	213,400
OH	-1,270	122,800	181,900
OK	-414	32,500	46,100
OR	523	30,400	41,100
PA	-783	133,200	168,500
RI	-120	11,000	15,000
SC	367	36,900	52,100
SD	-403	10,300	11,700
TN	144	61,000	90,600
TX	509	180,500	253,400
UT	-124	20,000	33,500
VA	718	67,900	109,200
VT	115	6,000	9,300
WA	1,049	56,700	85,300
WI	-318	58,100	78,200
WV	-99	18,800	25,200
WY	67	4,200	8,300

Exhibit 23: LPNs Average Annual Net Cross State Migration, 2015-2030

State	Average Annual Migration (Move-in Minus Move-Out)	Estimated 2015 FTE Supply	Projected 2030 FTE Supply
AK	51	1,700	2,000
AL	-49	22,200	20,500
AR	-69	12,200	17,800
AZ	165	9,100	12,200
CA	-542	72,000	121,000
CO	201	6,900	10,400
CT	8	9,600	11,000
DC	16	900	1,800
DE	24	2,900	4,200
FL	225	54,200	73,600
GA	193	26,300	25,800
HI	171	2,300	4,700
IA	-163	7,900	13,000
ID	55	2,500	4,300
IL	116	26,500	34,400
IN	31	19,900	19,900
KS	-105	8,400	14,400
KY	-136	12,600	14,400
LA	-57	18,400	20,700
MA	-47	14,400	16,500
MD	32	13,300	11,300
ME	59	2,000	3,400
MI	-121	21,500	24,800
MN	-126	16,200	24,700
MO	-126	20,000	23,200
MS	-79	9,900	11,800
MT	12	2,300	2,800
NC	55	22,900	24,400
ND	81	2,500	3,900
NE	-90	6,200	6,000
NH	34	4,700	4,700
NJ	-55	19,400	30,500
NM	103	3,000	4,900
NV	87	3,200	4,200
NY	-57	52,400	58,900
OH	-270	42,500	54,900
OK	-149	14,800	18,400
OR	-39	3,100	4,900
PA	-212	49,300	48,600
RI	46	2,000	2,300
SC	72	8,000	8,200
SD	-15	2,100	2,800
TN	109	24,000	29,600
TX	385	70,900	80,900
UT	-16	2,900	6,700
VA	84	25,500	32,200
VT	-2	1,800	2,500
WA	56	11,200	13,600
WI	-48	12,600	16,300
WV	114	7,600	10,900
WY	-15	1,000	1,800

5. Developing Nursing Demand Projections

The projected demand for nurses was derived from the common model outlined in Section III. Predicted probabilities were applied to the simulated micro-data set for future years to obtain projected service use specific to the settings that employ nurses. For example, projected growth in hospital inpatient days and emergency visits was used to project growth in demand for RNs and LPNs employed in hospitals. For work settings outside the traditional health care system, HWSM used the size of the population most likely to use those services to project demand (Exhibit 24).

The HWSM used provider staffing patterns to project demand for health care workers by delivery setting based on the demand for health care services. As illustrated in Exhibit 24, nurses were found in almost all care delivery settings. Nurse staffing patterns were calculated using the portion of national FTE nurses providing care in each setting, and dividing by current estimates of the workload driver in that work setting. The baseline demand projections assumed these ratios remained constant over time. The demand for nurses in academia was based on the estimated number of nursing graduates, assuming that current ratios of nurse educators-to-students remained constant. Estimates of the distribution of nurses across employment settings came from analysis of the 2015 Occupational Employment Statistics (OES) data collected by the Bureau of Labor Statistics. We used data from the 2008 National Sample Survey of Registered Nurses to break our hospital totals from the OES data into inpatient and emergency departments, and to break out nurses in education to those providing school health and those in nursing education.

National staffing ratios by care delivery setting at baseline were applied to the projected service use to obtain the staffing requirement by setting. These were aggregated to obtain the total demand for nurses. Projections were made at the state level and summed to produce national estimates.

Exhibit 24: Summary of Nursing Workload Drivers by Work Setting

	Distribution (%)		Full Time Equivalents		Workload[b]		Staffing Ratios *(workload per nurse)*	
	RNs[a]	**LPNs[a]**	**RNs**	**LPNs**	**Volume**	**Metric**	**RNs**	**LPNs**
Office	7.5	14.5	211,100	117,200	976,507,000	Visits	4,626	8,332
Outpatient	4.0	3.1	112,500	25,500	36,889,000	Visits	328	1,447
Inpatient	52.8	16.6	1,485,300	134,500	145,137,000	Days	98	1,079
Emergency	8.5	<0.1	236,600	--	119,144,000	Visits	504	--
Home Health Care[e]	6.3		178,500		228.5 million	Visits	1,280[c]	
		12.2		99,300	150.8 million	Visits		1,519[c]
Nursing Home[e]	5.6	31.3	156,700	252,200	19,769,000	Population 75+	126	78
Residential Care[e]	1.7	8.8	48,300	71,200	19,769,000	Population 75+	409	278
School Health	3.1	<0.1	85,700	--	49,788,000	Students	581	--
Nurse Education	3.6	0.3	101,000	2,100	158,000 (RNs) 51,000 (LPNs)	NCLEX 1st time US-educated takers	2.1 (RN+LPN)	24.3 (LPN)
All Other	6.8	13.0	190,400	117,700	318,857,000	Population	1,675	2,961
Total	**100**	**100**	**2,806,100 [d]**	**809,700[d]**				

Note: Numbers may not sum to 100 percent because of rounding. Sources: [a] BLS Occupational Employment Statistics 2015 (with RN distribution modified for nurse education, school health and emergency departments based on the 2008 National Sample Survey of Registered Nurses; [b] Estimates from HWSM; [c] Estimates based on working 240 days/year and 4.96 home health visits/day for RNs and 5.9 visits/day for LPNs. http://www.nahc.org/assets/1/7/10hc_stats.pdf Published estimates for national home health visits are unavailable, so the total visit estimates presented here were calculated based on published nurse workload data plus estimates of total nurses providing home health services.; [d] American Community Survey, 2014 ; [e] Staffing estimates for nurses in long term care settings were updated in 2017 (Exhibit 10).

6. Baseline and Alternative Nursing Workforce Projections

a) *Supply Projections*

HWSM can project future nurse supply under multiple scenarios to illustrate the sensitivity of the model to the continuation of trends in key supply determinants. The Status Quo scenario models the continuation of current numbers of nurses completing their nursing education and current patterns of labor force participation. As discussed previously, labor force participation (retirement, being temporarily out of the workforce, and hours worked patterns) varies by nurse demographics, education level, and other characteristics of the nurse or community. The Status Quo scenario models the continuation of these patterns taking into account the changing demographic and changing education levels of the nursing workforce.

Alternative supply scenarios modeled include the impacts of: 1) retiring two years earlier or delaying retirement by two years, on average; 2) graduating 10% more or 10% fewer nurses annually than the status quo; 3) and a gradual 5% increase or 5% decrease in average nurse productivity levels. The early or delayed retirement scenarios simply shift workforce attrition patterns for nurses age 50 and older by ±2 years. For example, a nurse who would have retired at age 65 under the Status Quo scenario would now retire at age 63 under the Early Retirement scenario and would retire at age 67 under the Delayed Retirement scenario. The ±5% change in productivity scenarios assume that each year between 2014 and 2030 there is small (about 0.31%) change in nurse productivity such that cumulatively the impact reaches ±5% impact by year 2030 versus year 2014. Productivity is defined for purpose of supply modeling as the number of patients that can be treated by 1 FTE nurse over the course of a year (as defined by the staffing levels in Exhibit 24). Productivity changes could occur because of changes in technology or practice patterns, or through changes in average hours worked. A ±5% productivity change is equivalent to ±5% change in FTE supply.

b) Demand Projections

The Baseline scenario for modeling demand assumes that recent (2009-2014) patterns of care use and delivery will remain unchanged, but takes into account population growth and aging as well as expanded insurance coverage that has occurred and is projected to occur under the Affordable Care Act. Care use and delivery patterns likely will change over time; however, there is limited published information or data to use for modeling how care use patterns might change over time and the nursing workforce implications of changes in care use or delivery. Using information from several published demonstrations of emerging care delivery models, we simulated the potential impact of such changes on the nursing workforce.

The following examples combine information from the published literature with the HWSM to illustrate the changing roles of RNs and LPNs within a care coordination model. These models are currently part of ongoing studies on nurse utilization in coordinated care settings. Each pilot study utilizes RNs in roles such as nurse care managers working with other staff to coordinate care, improve patient self-education and adherence to treatment plans.

The pilot studies also illustrate how RN care managers coordinate with pharmacists, behavioral health providers, and licensed clinical social workers. Under the shifting roles of RNs in these and other emerging care models focused on improving population health, service demand is reduced and redirected from higher cost hospital inpatient and emergency department settings to more clinically appropriate outpatient and community-based care settings. As a result, some future reductions in clinical RN staffing in hospital settings are possible.

The Camden Coalition (Camden, New Jersey) provides health services to a patient population that experiences multiple social barriers to accessing health services. [30] RNs are utilized in care manager roles to provide critical support and oversight for patients' transition into primary care. Camden Coalition's RN model focuses on patient engagement; patient care is tailored to the specific needs of each patient to ensure a more effective transition into primary care. To date, hospital admissions by "super users," or patients who frequently utilize hospital services, declined by 57%, while emergency department visits declined by 33% and the cost of care decreased by 56%.[31] The nursing workforce implications of implementing such a model at the national level could be reductions in demand of about 158,000 RNs and 14,000 LPNs in hospital settings in 2030, assuming super users account for 4% of all visits to the emergency room[32] and 14% of inpatient hospital days.[33]

CareOregon (Portland, Oregon) is a non-profit Medicaid managed care plan which serves 128,000 low-income residents representative of one-third of the state's Medicaid enrollees. [34] Two-thirds of patients have one of 12 common chronic conditions including but not limited to diabetes, depression, and chronic heart failure. Two-thirds of the health plan members are children and more than 5,700 adults are dual-eligible for Medicaid and Medicare services. CareOregon provides two health care tracks: (1) *Primary Care Renewal* (a patient-centered medical home initiative) works through safety net clinics; and (2) *Care Support*, a multidisciplinary management program for members with high risk of poor health outcomes. Both health care tracks utilize nurse care managers on care coordination teams working with social workers and care coordination assistants to monitor patients and identify risks before health crises occur. Nurse care managers' functions include coordination of services, patient education, and treatment adherence. Care Support reported decreases in non-obstetric hospital admissions and emergency department visits of about 34%. Offering such a model to all Medicaid beneficiaries nationally could result in lower hospital-based RN and LPN FTE demand

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[30] Camden Coalition of Healthcare Providers: Outreach to High Utilizing Patients – Basics of Care Management and Care Transitions in Camden, NJ. *PowerPoint Presentation*. Retrieved from: https://www.camdenhealth.org/wp.../CMT-CT_overview_webinar-1.pptx

[31] Hong, C. S., Siegel, A. L., & Ferris, T. G. (2014). Caring for high-need, high-cost patients: what makes for a successful care management program? *Issue Brief (Common Wealth Fund)*, *19*, 1-19.

[32] Castillo, EM,. Brennan, JJ., Chan TC., Killeen, JP., UC San Diego. (2012). *Factors Associated with Frequent Users of Emergency* Department *Resources* [Fact Sheet]. Retrieved from https://www.acep.org/uploadedFiles/San%20Diego%20frequent%20users%20general.pdf

[33] Pennsylvania Health Care Cost Containment Council. (2014). *Pennsylvania's "Super-Utilizers" of Inpatient Hospital Care* [Fact Sheet]. Retrieved from http://www.phc4.org/reports/researchbriefs/super-utilizers/2014/docs/researchbrief_super-utilizers_2014.pdf

[34] D Dorr. Teamwork and Medical Home in Rural Settings; A Case Study with Care Management Plus, *Presentation for the Oregon Health and Science University*, Sept. 2008: http://caremanagementplus.org/documents/Me33icalHomeOverview_Dorr.pdf

in 2030 by about 151,000 and 11,000, respectively, resulting from lowered levels of service use in the inpatient and emergency settings.

Community Care of North Carolina (CCNC) (Raleigh, North Carolina) utilizes nurses as managers in the provision of services for chronically ill patients. [35] The patient population includes the Aged, Blind, and Disabled sub-population which accounts for nearly 70% of the service dollars but fewer than 30% of program recipients. Nurse care managers work with physicians and pharmacists to provide coordinated patient care. Duties include but are not limited to: medication reconciliation, coordination with medical homes and primary care providers providing patient care and with community agencies and other local resources providing support services for the Medicaid population. CCNC reported the following results between 2006 and 2011: (1) admission rates decreased by 21%; and (2) emergency department visits decreased by 32.8%. Implementing this program for a similar national Medicaid population could reduction the projected 2030 FTE demand for hospital-based RNs and LPNs by about 103,000 and 7,000, respectively.

These illustrative examples of pilot studies using nurses to better manage patient care illustrate that while demand for nurses might rise for some roles (e.g., care management), the overall demand for nursing services could fall in hospital settings. In general, the literature suggests that the decline in nurses resulting from lower health care utilization will more than exceed the increase in demand for nurses for care management. Hence, the demand projections presented in this report might be high and thus understate projected surpluses if current supply trends continue.

Population Health

While the above pilot studies focus on the short-term implications on care utilization and staffing among select high-utilization subsets of the population, there are broader trends in population health that have long term implications for the nurse workforce. New policy guidelines, provisions in the ACA, and new reimbursement models are designed to promote preventive care with the potential to improve the health of the entire population (beyond just high risk, high utilization subpopulations). Examples include guidelines and reimbursement for counseling and treatment to promote a healthful diet and physical activity to individuals at high risk for

[35] Dobsen, L. and D. Hewson. Community Care of North Carolina – An Enhanced Medical Home Model. *NC Med J* May/June 2009: 70: 219-224

developing cardiovascular disease or diabetes, for smoking cessation, and to improve control of blood pressure, cholesterol levels, and hemoglobin A1c levels.[36,37,38]

Building on a recently published study[39] and using a Markov-based microsimulation approach described in detail elsewhere[40,41] we modeled the potential long term health impacts and nurse demand of achieving the following population health goals:

- **Sustained 5% body weight loss for overweight and obese adults**: Counseling and pharmacotherapy have been shown to reduce excess body weight by 5% or more—thus lowing risk for diabetes, cardiovascular disease, and other morbidity.[42]
- **Improved blood pressure, cholesterol, and blood glucose levels**: Published trials report that among patients with elevated levels, counseling and pharmacotherapy can improve cholesterol, blood pressure, and hemoglobin A1c levels.[43,44,45]
- **Smoking cessation**: Smoking cessation can reduce risk for cancer, heart disease and other morbidity.[46]

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[36] USPSTF Final Recommendation Statement Obesity in Adults: Screening and Management. Retrieved from https://www.uspreventiveservicestaskforce.org/Page/Document/RecommendationStatementFinal/obesity-in-adults-screening-and-management. USPSTF Final Recommendation Statement Healthful Diet and Physical Activity for Cardiovascular Disease Prevention in Adults With Cardiovascular Risk Factors: Behavioral Counseling. Retrieved from https://www.uspreventiveservicestaskforce.org/Page/Document/RecommendationStatementFinal/healthy-diet-and-physical-activity-counseling-adults-with-high-risk-of-cvd.

[37] CMS. Medicare Preventive Services, 2016. Retrieved from https://www.cms.gov/Medicare/Prevention/PrevntionGenInfo/Downloads/MPS-QuickReferenceChart-1TextOnly.pdf

[38] U.S. Department of Health & Human Services. Preventive Services Covered Under the Affordable Care Act. Retrieved from https://www.hhs.gov/healthcare/facts-and-features/fact-sheets/preventive-services-covered-under-aca/ https://aamc-black.global.ssl.fastly.net/production/media/filer_public/a5/c3/a5c3d565-14ec-48fb-974b-99fafaeecb00/aamc_projections_update_2017.pdf

[39] IHS Markit, *The Complexities of Physician Supply and Demand 2017 Update: Projections from 2015 to 2030*. Prepared for the Association of American Medical Colleges. Washington, DC: Association of American Medical Colleges. Retrieved from https://aamc-black.global.ssl.fastly.net/production/media/filer_public/a5/c3/a5c3d565-14ec-48fb-974b-99fafaeecb00/aamc_projections_update_2017.pdf.

[40] Dall, T.M., Storm, M.V., Semilla, A.P., Wintfeld, N., O'Grady, M., Narayan, K.M. (2015) Value of lifestyle intervention to prevent diabetes and sequelae. *Am J Prev Med* 48: 271-280.

[41] Su, W., Huang, J., Chen, F., Iacobucci, W., Mocarski, M., Dall, T.M., Perreault, L. (2015) Modeling the clinical and economic implications of obesity using microsimulation. *J Med Econ* 18: 886-897.

[42] Su, W., Huang, J., Chen, F., Iacobucci, W., Dall, T.M., Perreault, L. Return on Investment for Digital Behavioral Counseling in Patients with Prediabetes and Cardiovascular Disease. *Prev Chronic Dis*. 2016; 13; 150357.

[43] Huffman, T.F., Macedo, A.F., et al. Statins for the primary prevention of cardiovascular disease. *Cochrane Database Syst Rev*. 2013;1:CD004816. 2010;33(8):1859-1864.

[44] Baguet, J.P., Legallicier, B., Auquier, P., Robitail, S. Updated meta-analytical approach to the efficacy of antihypertensive drugs in reducing blood pressure. *Clin Drug Investig*. 2007;27(11):735-753.

[45] Sherifali, D., Nerenberg, K., Pullenayegum, E., Cheng, J.E., Gerstein, H.C. The effect of oral antidiabetic agents on A1C levels: a systematic review and meta-analysis. *Diabetes Care*. 2010; 33(8):1859-1864.

[46] Yang, W., Dall, T.M., Zhang, Y., Zhang, S., Arday, D.R., Dorn, P.W., and Jain, A. Simulation Of Quitting Smoking In The Military Shows Higher Lifetime Medical Spending More Than Offset By Productivity Gains. *Health Affairs*. 2012; 31(12): 2717-2726.

The model's prediction equations came from published clinical trials and observational studies, and the simulation was conducted using a nationally representative sample of adults constructed using the 2013-2014 National Health and Nutrition Examination Survey combined with national population projections. Outcomes from this model were then used in the HWSM to model the demand for health care services and nurses.

As reported elsewhere[39], cumulative between 2015 and 2030, achieving these population health goals could reduce cases of heart disease by 10.2 million, stroke incidence by 3.2 million, myocardial infarction incidence by 3 million, and incidence of cancer and other diseases. This reduction in incidence/prevalence would reduce demand for nurses. However, the improved health of the population would also reduce mortality, and if the modeled goals were achieved the projected size of the population in 2030 would be 6.3 million higher than current Census Bureau projections. These additional 6.3 million people would be primarily elderly—including about 2.9 million age 75 or older, 2.3 million age 65 to 74, 1 million age 45 to 64, and approximately 30,000 adults under age 45.

Compared to the baseline demand scenario, by 2030 national demand for RNs and LPNs under this population health scenario would be *higher* by approximately 105,800 FTEs and 69,500 FTEs, respectively, to support the larger population even though per capita use of nursing services would be lower. This scenario suggests that efforts to improve population health might reduce demand for nurses in the short term, but to the extent that preventive care increases longevity overall demand for nurses could rise in the long term.

c) Modeling Supply and Demand by Metropolitan versus Non-metropolitan Location

State-level indicators of metropolitan/non-metropolitan for modeling nurse supply in 2014 came from analysis of the ACS. Using USDA 2013 Rural-Urban Continuum Codes (RUCC) we classified each county or county subpart in a PUMA as metropolitan or non-metropolitan.[47] Metro and non-metro county classifications are based on Office of Management and Budget (OMB) delineation as of February 2013. OMB defines metro counties with RUCC values of 1,2, or 3 and all other counties are defined as non-metro. The Rural-Urban Continuum Codes (RUCC) file was merged with the PUMA-county crosswalk file available through the Missouri

[47] United States Department of Agriculture, Economic Research Service. Rural-Urban Continuum Codes. Accessed April 6, 2017 at: https://www.ers.usda.gov/data-products/rural-urban-continuum-codes.aspx#.UYJuVEpZRvY.

Data Center which allows us to map PUMA to a county.[48] Thus we were able to assign a PUMA as either metro or non-metro based on the RUCC definitions. Finally, the PUMA-county crosswalk file including the metro/non-metro indicator was merged with the ACS file in order to generate statistics by metro and non-metro.

Indicators of metropolitan/non-metropolitan to model demand for nurses is based each person's metropolitan status as indicated in the BRFSS. Metropolitan status was based on the "MSCODE" variable in the 2013-2014 BRFSS survey data. Based on the BRFSS variable metropolitan area is defined where one of the following criteria is fulfilled: 1) In the center city of an MSA; 2) Outside the center city of an MSA but inside the county containing the center city; 3) Inside a suburban county of the MSA; or 4) In an MSA that has no center city.

Given the demographics and health care use patterns of the population in metropolitan versus non-metropolitan areas, the population living in metropolitan areas would utilize approximately 83% of the nation's RN services. An estimated 85% of FTE RN supply is in metropolitan areas. Though the 83% and 85% are similar, many patients in non-metropolitan areas might travel to metropolitan areas to receive specialized care, and nurse staffing patterns could differ between metropolitan and non-metropolitan areas both to reflect differences in patient acuity levels and differences in productivity due to patient volume.

C. Behavioral Health Care Provider Model (updated 2015)

Behavioral health care is a term that covers the full range of any behavioral problem, including mental health and substance abuse conditions, stress-linked physical symptoms, patient activation and health behaviors. In 2014-2015, HRSA updated the behavioral health component of HWSM and added the following five occupations: substance abuse and behavioral disorder counselors (addiction counselors), mental health and substance abuse social workers (clinical social workers), mental health counselors, school counselors, and marriage and family therapists.[49] There is substantial overlap in the types of services provided by the above behavioral health providers.

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[48] Missouri Census Data Center, MABLE/Geocorr v. 1.2, 2012: Geographic Correspondence Engine. Web application accessed April 6, 2017 at: http://mcdc.missouri.edu/websas/geocorr12.html

[49] Brief descriptions of each occupation come from the Bureau of Labor Statistics http://www.bls.gov/ooh/community-and-social-service/home.htm

1. Estimating the Base Year Workforce Supply

The sources for data on current supply were the 2013 AMA Master File for psychiatrists; the 2013 NCCPA Master File for physician assistants; the 2012 NSSNP and 2013 NPPES for nurse practitioners; the 2013 ACS for psychologist; and the 2013 ACS and the 2013 BLS Occupational Employment Statistics (OES) for counselors, social workers, and technicians. State-level data from the OES were used to estimate the number of social workers and counselors who employed as behavioral health professionals. The age and gender distributions of behavioral health professionals with graduate degrees were used as proxy for the age and gender distribution of for counselor and social worker occupational categories. The resulting person-level provider files were then used in the microsimulation model.

2. Modeling New Entrants to the Behavioral Health Workforce

Supply projections account for new behavioral health professionals that enter the workforce each year. As detailed in Section II B, a synthetic population was created for use in HWSM, which reflected the number, and age-gender distribution of new graduates annually in the occupation (Exhibit 25).

Exhibit 25: Age and Sex Distribution of New Behavioral Health Professionals

<table>
<tr><th rowspan="2">Licensed Health Workers</th><th rowspan="2">Annual No of Graduates</th><th rowspan="2">Female (%)</th><th colspan="4">Age Distribution (%)</th></tr>
<tr><th>≤25</th><th>26-30</th><th>31-40</th><th>≥41</th></tr>
<tr><td>Psychologists</td><td>5,744</td><td>68%</td><td>5%</td><td>71%</td><td>22%</td><td>2%</td></tr>
<tr><td>Mental health counseling/counselor</td><td>5,038</td><td>83%</td><td rowspan="5">40%</td><td rowspan="5">22%</td><td rowspan="5">25%</td><td rowspan="5">13%</td></tr>
<tr><td>Marriage and family therapy/counselor</td><td>662</td><td>83%</td></tr>
<tr><td>Substance abuse/addiction counselor</td><td>3,623</td><td>73%</td></tr>
<tr><td>Education/ school counselor</td><td>5,631</td><td>84%</td></tr>
<tr><td>Clinical/medical social worker</td><td>2,462</td><td>88%</td></tr>
</table>

Sources: Annual graduates and percent female from 2013 IPEDS. Age distribution for new counselors and social workers in behavioral health reflects age of students in master's level social worker programs. Council of Social Work Eduction. 2013 Statistics on Social Work Education in the United States. https://www.cswe.org/Research-Statistics/Research-Briefs-and-Publications/2013-Statistics-on-Social-Work-Education-in-the-Un.aspx

3. Modeling Workforce Participation

Labor force participation rates for all licensed behavioral health professionals were calculated directly for individuals through age 50 using 2013 ACS data. Because social workers and counselors working in behavioral health were not identifiable in ACS, data on the broad social workers and counselors group were used as a proxy for workforce participation patterns of social workers and counselors in behavioral health services. ACS does not capture occupation for individuals out of the workforce for five years or more, making it difficult to estimate the denominator for the rates. Information on workforce participation by education was used to estimate the retirement pattern for workers over age 50. Age gender specific activity rates for individuals with a graduate degree (masters level or higher) were used to model retirement patterns for counselors and social workers over age 50. Retirement patterns for psychiatrists were derived from Florida's 2012-2013 Physician Survey and applied nationwide.

4. Modeling Hours Worked

Estimates for weekly hours work for behavioral health counselors and clinical social workers came from Ordinary Least Squares (OLS) regression equations on 2008-2013 ACS data. Because the ACS does not distinguish types of counselor and social worker, data on employed individuals with a graduate degree were used as proxy. The dependent variable in the regressions was the log of hours worked in the previous week, and explanatory variables included age group, sex, log of expected hourly earnings, state-level estimate of the overall unemployment rate, and a year indicator. Wages and unemployment rates were introduced as time varying covariates and were derived from the BLS state-level estimates for each of the years between 2008 and 2013. The projected number of hours worked by each individual was converted to FTE supply by dividing the total person-hours worked by the average number of hours worked per week for counselors and social workers employed at least 20 hours per week in the base year.

Data for modeling hours worked patterns of psychiatrists come from analysis of Florida's 2012-2013 Physician Survey. Data on PAs in mental health came from the 2013 National Commission on Certification of Physician Assistants (NCCPA) Master File; data for NPs in mental health came from the 2012 National Sample Survey of Nurse Practitioners (NSSNP) for NPs employed at least 20 hours per week. The approach to modeling hours worked patterns for psychiatrists, PAs, and NPs used OLS regression analysis where log of hours worked per week in patient care activities was the dependent variable. Explanatory variables were dummy variables for each medical specialty, clinician age groups, sex, and interaction terms between age and sex.

5. Modeling Behavioral Health Demand Projections

To determine the demand for behavioral health services of HWSM, the MEPS Visit Files from 2008-2012 were analyzed. Poisson regressions for each type of service visits were estimated for adults and children separately. The dependent variables were annual visits to each type of behavioral health professional. Explanatory variables consisted of the demographic, economic, insurance, health status, and health behavior variables described in Section III A.

Because family therapists are not listed among the MEPS occupation codes, the information of mental health and substance abuse counseling where the person had at least one visit during the year was analyzed as a proxy for demand for family therapy services. MEPS also does not specifically identify mental health counselors as an occupation, so visits with a mental health diagnosis code for occupations in the "other non-physician specialist" category was analyzed. Likewise, MEPS does not specifically identify addiction counselors in the occupation list. The regression for addiction counselor includes all visits where the occupation indicated "other non-physician specialist" and the visit had an indication code that alcohol or drug abuse counseling or treatment was provided.

To account for the demand for behavioral health workers, national estimates of total FTE providers in each care delivery setting was estimated. Total workload measures were divided by FTE supply in 2013 to calculate staffing ratios by occupation and care delivery setting (see Appendix, Exhibit A-1). The Baseline demand scenarios assumed that the current demand for providers were met exactly by the providers available in each setting nationally and that the provider-to-visits ratio will remain unchanged during the projection period. It was also assumed that behavioral health service delivery in each state followed the national patterns.

In addition to the baseline scenario, an alternative scenario was developed to assess current and projected effects of unmet the demand for behavioral health care, using information that indicates approximately 20 percent of the 2013 U.S. population may have needed but did not receive treatment for mental illness, substance use, and/or substance dependence in 2013. Assuming that the only barrier to access behavioral health services for this population was lack of providers, 2013 demand estimates for services and providers would need to be inflated, consequently, the 2025 demand projections developed would also be correspondingly higher.

Development of the alternative unmet demand scenario relied on data from SAMHSA's 2013 National Survey on Drug Use and Health, which found an estimated 43.8 million U.S. adults had any mental illness in the past year, yet only 19.6 million of those 43.8 million received mental health services.[50] SAMHSA also estimated that 22.7 million adolescents and adults needed treatment for an illicit drug or alcohol use problem, yet only 2.5 million of those 22.7 million

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[50] U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration. 2014. Results from the 2013 National Survey on Drug Use and Health: Mental Health Findings, NSDUH Series H-49, HHS Publication No. (SMA) 14-4887. Rockville, MD. Accessed 11/16/2015: http://www.samhsa.gov/data/sites/default/files/NSDUHmhfr2013/NSDUHmhfr2013.pdf.

received treatment at a specialty facility and only 4.1 million people received any treatment for a problem related to the use of alcohol or illicit drugs.[51]

These estimates suggest that between 40 million and 45 million individuals (roughly 20 percent of the U.S. 2013 population[52]) may have needed but did not receive behavioral health care in 2013.

D. Primary Care Provider Model

This section summarizes the methodology for projecting the supply and demand for primary care physicians, advanced practice nurses (APNs) and physician assistants (PAs) at the national, U.S. census division and region levels by specialty. Selected specialties identifying primary care providers include general and family medicine, general internal medicine, geriatrics, and general pediatrics.

1. Estimating the Current Active Workforce Supply

The source for estimating the current active supply of physicians at the U.S. region and state level is the 2013 American Medical Association (AMA) Master File Extract. The analysis was limited to active physicians. Because the AMA file is known to misclassify older physicians who have retired as 'active', those over age 75 were deleted from the analysis file. In addition, retired physicians between 50 to 75 years of age were identified and deleted based on predicted probabilities derived from a logistic regression on age and specialty. In addition to adjusting for misclassification of retirees as active physicians, the AMA Masterfile was adjusted for undercounting hospitalists, a large proportion of who are listed under the specialty in which they received their training.

The method to separate hospitalists trained in primary care from physicians actually providing office-based primary care services builds on ongoing work by AAMC's Center for Workforce Studies. Using the NPI numbers from 2014 Medicare fee-for-service billing records and the AMA Masterfile, physicians where close to 100% of their Evaluation and Management billing

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[51] U.S. Department of Health and Human Services, Substance Abuse and Mental Health Services Administration. 2014. Results from the 2013 National Survey on Drug Use and Health: Summary of National Findings, NSDUH Series H-48, HHS Publication No. (SMA) 14-4863. Rockville, MD. Accessed 11/16/2015: http://www.samhsa.gov/data/sites/default/files/NSDUHresultsPDFWHTML2013/Web/NSDUHresults2013.pdf.

[52] U.S. Department of Commerce, Bureau of the Census. U.S. 2013 Population. Accessed Nov 16, 2015: http://factfinder.census.gov/faces/tableservices/jsf/pages/productview.xhtml?src=bkmk. [Adolescent/adult population = 267.56 million]

was hospital-based were identified as hospitalists in the AMA Masterfile. About twenty five thousand hospitalist physicians were listed in the AMA Masterfile as general internists, family physicians, or geriatricians. Hospitalists trained in pediatrics could not be identified using Medicare billing records. A comparison of the counts from the original AMA file with the new file with hospitalists removed provided the discount factor. The base numbers in 2013 AMA Masterfile were then discounted by that factor.

The base year counts for APNs come from the 2013 National Plan and Provider Enumeration System (NPPES) which contains a unique identifier (National Provider Identification, NPI) for each clinician. The 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey was utilized to develop the base year counts for PAs by age and gender.

2. Modeling New Entrants

The mechanism for adding new entrants to the workforce each year is the creation of a "synthetic" population of the occupation based on the number and characteristics of recent graduates in each occupation. As described in Section II B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years.

Estimates of total annual new physicians, APNs, and PAs and the specialty distribution came from multiple sources. The primary sources of data on characteristics of new graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators, the 2013 AMA Master File and the American Board of Medical Specialties (ABMS) for physician specialties. Numbers and characteristics of new NPs, in the workforce entrants come from the 2012 American Association of Colleges of Nursing (AACN) survey. The 2013 NCCPA Professional Profile is the primary source for characteristics on new PA workforce entrants and the Physician Assistants Education Association the source of data on new PAs trained. Exhibit 26 summarizes the age and sex distribution of new entrants to the primary care workforce.

After simulating the age and sex of the new entrants, the state where new providers would practice was simulated based on a model that regressed the probability of practicing in a state on the relative difference between the projected supply and demand for services for that kind of provider in that state.

Exhibit 26: Age and Sex Distribution of New Physicians, APNs and PAs in Primary Care

Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution <25	26-30	31-40	>41
Primary Care Physicians						
General & Family Medicine	3,270	55%	0%	30%	60%	9%
General Internal Medicine	3,301	44%	0%	34%	60%	7%
Geriatrics	279	58%	0%	15%	77%	8%
General Pediatrics	1,642	71%	0%	49%	48%	3%
Total	29,032	45%	0%	18%	75%	7%
Advanced Practice Nurses & Physician Assts.						
Nurse Practitioner	6080[a]	95%	2%	22%	32%	44%
Physician Assistant	2,182 -2,570[b]	64%	9%	38%	42%	11%

Sources: 2013 AMA Master File, 2012-2013 AAMC GME Census,2012 American Association of Colleges of Nursing (AACN) survey, 2013 NCCPA Professional Profile, Physician Assistance Education Association. [a] Estimates of new NPs trained reflect analysis of the 2012 NSSNP of the proportion of new NPs in primary care that work in a position requiring NP licensure. [b] Grows from 2,128 to 2,570 between 2013 and 2025 reflecting projected growth in number and average size of PA programs. Primary sources of data on new graduates include the AMA Masterfile for physicians, PAEA and the NCCPA for Physician Assistants, and the AACN for APNs.

3. Modeling Workforce Attrition

Data sources for modeling retirement patterns of physicians by individual specialty are limited. The primary source of retirement information for physicians in HWSM is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire in the upcoming five years. The retirement patterns from this source were compared to the AAMC's 2006 Survey of Physicians over Age 50 which collected information on age at retirement or age expecting to retire and found to be comparable. However, the Florida survey was used because it has a larger sample size and more detailed information on individual specialties.

Retirement rates also differ by medical specialty. This analysis used the age, gender and specialty specific retirement rates from the 2012 and 2013 Florida Bi-annual Physician Licensure Survey to calculate the retirement rates for physician providers with primary care specialties. Retirement patterns for APNs and PAs were unavailable. As a result, retirement patterns for primary care physicians were used as proxies. Retirement patterns were combined with age-gender specific mortality rates from the Centers for Disease Control and Prevention (CDC) adjusted downward to account for lower mortality of technical and professional occupations.[53,54]

[53] Arias E. United States life tables, 2008. National vital statistics reports' vol 61 no 3. Hyattsville, MD: National Center for Health Statistics; 2012.

[54] Johnson NJ, Sorlie PD, Backlund E. The impact of specific occupation on mortality in the US National Longitudinal Mortality Study. Demography; 1999 Aug; 36:355-367.

4. Modeling Hours Worked

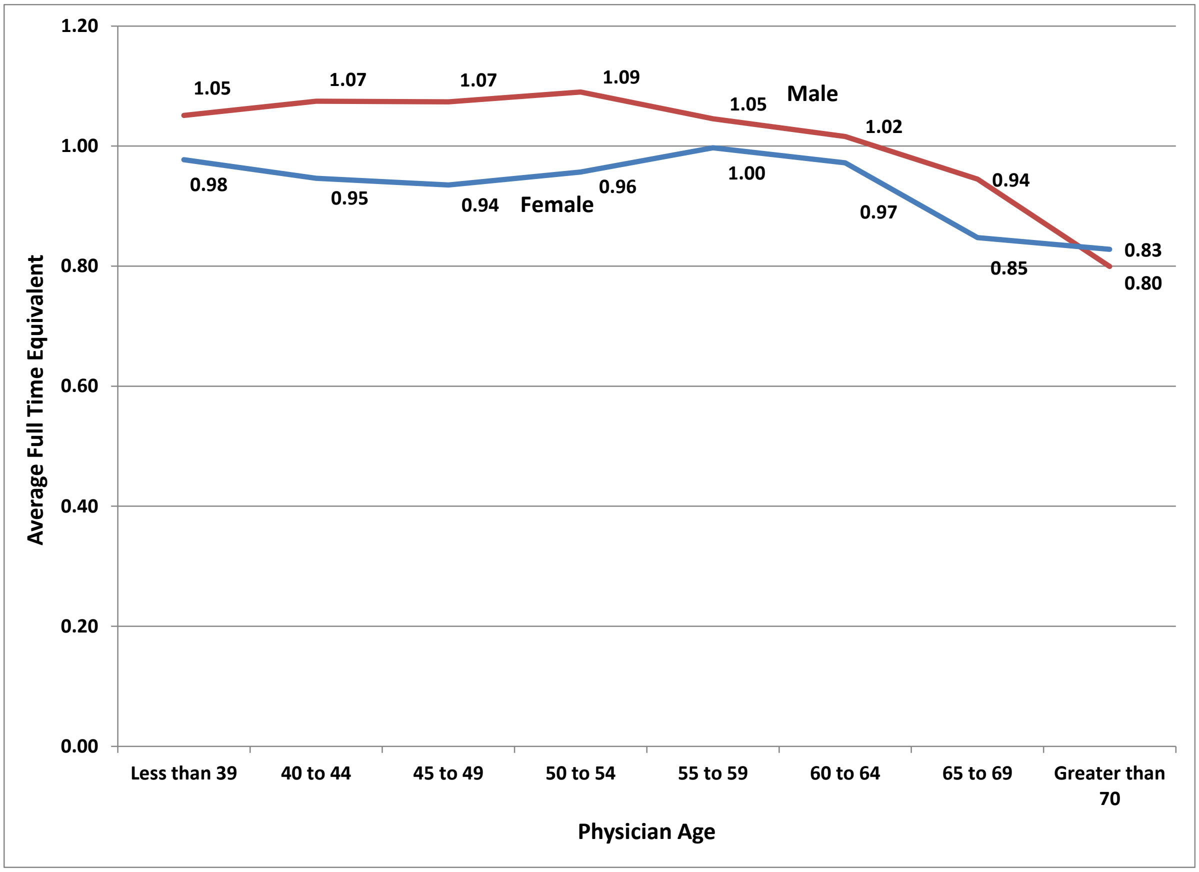
Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey (n=18,016) of physicians in Florida who renewed their license.[55] Hours worked patterns differed by specialty in addition to age and sex. Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable. Explanatory variables included indicator variables for specialty, age group, female gender, and age-group by gender interaction. Average hours worked by primary care physicians varied by specialty. FTE for primary care physicians for each specialty was defined as the average hours worked per week in that specialty. These were 40.4 hours for physicians in family practice, 44 hours for general internists, 40.5 for pediatricians and geriatricians. Exhibit 27 shows the hours worked pattern by physician age and sex. Young, male physicians tended to work more hours per week than their female counterparts, while the gender gap in hours worked largely disappeared after age 55.

Similar regression analyses were conducted using 2013 NCCPA licensure files to model hours worked patterns of PAs, and the 2012 National Sample Survey of Nurse Practitioners **(***NSSNP***)** to model hours worked patterns for NPs. However, no sex-by-age interaction terms were included for APNs because the large majority is female. An FTE was calculated for these occupations as the average hours worked among clinicians working at least 20 hours per week.

On average, NPs in primary care worked 32 hours weekly in patient care related activities. Average weekly hours worked patterns varied slightly across PA primary care specialties, ranging from 39 hours (pediatrics) to 42 hours (general internal medicine and geriatrics). PAs in general family practice worked on average about 41 hours weekly.

55 Analysis of Maryland's physician licensure files found similar work patterns by physician age, sex, and specialty

Exhibit 27: Primary Care Physician Hours Worked Patterns, in FTEs



Sources: Florida 2012-2013 bi-annual Physician Licensure Workforce Survey

5. Developing Primary Care Physician, APN and PA Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians, APNs and PAs was derived from the common model outlined in Section III. Predicted probabilities were applied on the simulated micro-data set for future years through 2025 to obtain projected service use specific to the settings where these providers work. For work settings outside the traditional health care system (e.g., school health) HWSM used the size of the population most likely to use those services. Due to small sample sizes HWSM does not model occupation-setting combinations where service volume is small (e.g., physicians providing care in home health and residential facilities). Also, the proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time.

Demand for primary care physicians was tied to projected demand for office visits. In addition, the demand was tied to a specific proportion of inpatient services to account for hospital rounds conducted by primary care physicians.

Prediction equations for use of office and outpatient services were estimated using Poisson regression with 2008-2012 MEPS data. Separate regressions were estimated for children and adults, and by physician specialty. The dependent variables were annual office visits and annual outpatient visits for each specialty. Explanatory variables consisted of the patient characteristics, socioeconomic and insurance variables, and health status variables described previously.

To account for the demand for primary care clinicians for hospital rounds, HWSM developed predictive equations for inpatient days by relevant population groups. For example, the demand for Geriatricians was derived from the expected number of hospital days in the 75 plus age group, while the demand for Pediatricians in a hospital was derived from the expected number among the 18 and younger age group (Exhibit 28).

Exhibit 28: Hospital Inpatient Demand Drivers by Primary Care Physicians

Medical Specialty	Workload Driver
Family Practice	Inpatient days for all hospitalizations
General Pediatrics	Inpatient days for all hospitalizations by patients age <18
Internal Medicine	Inpatient days for all hospitalizations by patients age 18+
Gerontology	Inpatient days for all hospitalizations by patients age 75+

Source: HWSM estimates from the Medical Expenditure Panel Survey (2008-2012) and the 2012 Nationwide Inpatient Sample

Predicted number of inpatient days were developed using the common methodology described in Section III.B.1 of this report, and aggregated across the relevant population groups. Current national estimates of the workload driver for primary care services and physician distribution are shown in Exhibit 29.

Exhibit 29: Summary of National Physician Workload Measures for Primary Care, 2013

	Office Visits	Outpatient Visits	Inpatient Days
Primary Care Services			
General & Family Practice	214,093,000	5,542,000	183,050,000 [a]
General IM	139,668,000	887,000	135,154,000 [b]
Pediatrics	130,940,000	614,000	47,896,000 [c]
Geriatrics	1,069,000	28,000	37,523,000 [d]
Primary Care Physicians			
General & Family Practice	90,260	2,250	2,280
General IM	73,290	420	19,830
Pediatrics	44,310	210	4,380
Geriatrics	2,640	70	870
Physician Staffing Ratio			
General & Family Practice	2,372	2,463	80,285
General IM	1,906	2,112	6,816
Pediatrics	2,955	2,924	10,935
Geriatrics	405	400	43,130

Sources: HWSM Projections for 2013 and analysis of 2013 AMA Master File. Distributions by care delivery site based on multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey, 2010 American Board of Internal Medicine survey, specialty-specific surveys.
Notes:. [a] All hospitalizations. [b] All hospitalizations by patients age <18, [c] All hospitalizations by patients age 18+, [d] All hospitalizations by patients age 75+.

The HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting (Exhibit 29). These ratios were then applied to projections of future demand for services that assumes the status quo in terms of care use and delivery patterns. Estimated FTE requirements to care for each person were then aggregated and inflated by the number of Physicians required to overcome primary care provider shortages in Health Professions Shortage Areas (HPSA)[56] to obtain the total demand for primary care physicians.

Because of limitations in identifying which visits/hospitalizations resulted in consultation with a NP and because NPPES, the data source used to determine the baseline NP supply did not identify the practice site, the demand for NPs in primary care were assumed to grow in the same

[56] U.S. Department of Health and Human Services, Health Resources and Services Administration 2013 Primary Medical Care HPSA Designation Overview. Available at http://bhw.hrsa.gov/shortage/hpsas/designationcriteria/primarycarehpsaoverview.html accessed September 22, 2015.

rate as the demand for primary care physicians. This implies that the physician to NP staffing ratio remains the same for the duration of the projection period.

However, for PAs, a process similar to estimating the physician staffing ratio was used to estimate current and project future FTE demand for PAs. Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each primary care delivery setting and specialty, and the national volume of care in each care setting and specialty, divided by the number of FTE PAs in that setting, provided estimates of PA FTE required per unit of health care service delivered in that setting (Exhibit 30).

Exhibit 30: Summary of FTE Physician Assistant Distribution by Care Delivery Site for Primary Care, 2013

Specialty	Office	Outpatient	Inpatient
Primary Care Services			
General & Family Practice	214,093,000	5,542,000	183,050,000 [a]
General IM	139,668,000	887,000	135,154,000 [b]
Pediatrics	130,940,000	614,000	47,896,000 [c]
Geriatrics	1,069,000	28,000	37,523,000 [d]
Primary Care Physician Assistant			
General & Family Practice	11,000	10,230	210
General Internal Medicine	3,870	2,490	920
General Pediatrics	1,800	840	530
Geriatrics	60	80	30
Primary Care Physician Assistant Staffing Ratio			
General & Family Practice	19,463	542	871,667
General Internal Medicine	36,090	356	146,907
General Pediatrics	72,744	731	90,370
Geriatrics	17,817	350	1,250,767

Source: HWSM Projections for 2013 and Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey.
Notes: [a] All hospitalizations. [b] All hospitalizations by patients age <18, [c] All hospitalizations by patients age 18+, [d] All hospitalizations by patients age 75+.

E. Internal Medicine Subspecialty Model

This section describes the supply and demand models of physicians and PAs in 11 internal medicine subspecialties (Exhibit 31) and the supply and demand for physicians and nurse practitioners in critical care medicine. Estimating the Current Active Workforce Supply

The source for estimating the current active supply of physicians at the U.S. state and region level is the 2013 American Medical Association (AMA) Master File Extract adjusted for misclassification of older (aged 75 or over) retired physicians as “active”. The base year counts and age sex characteristics for PAs come from the 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey. The counts for NPs in critical care come from NPPES, while the age sex distribution of from the ACS is used to assign the age-sex characteristics.

Exhibit 31: Summary of Internal Medicine Specialties

Specialty	**Description**
Allergy and Immunology	The prevention, diagnosis and treatment of problems with the immune system.
Cardiology	The diagnosis, intervention, treatment, and care of the heart and its related diseases.
Critical Care[a]	The treatment and care of a critically ill or critically injured patient. Critical illness acutely impairs one or more vital organ systems such that there is a high probability of imminent or life threatening deterioration in the patient's condition.
Dermatology	The diagnosis, treatment, and prevention of diseases of the skin, hair, nails, oral cavity and genitals.
Endocrinology	The diagnosis and treatment of diseases related to hormones and human functions as the coordination of metabolism, respiration, reproduction, sensory perception, and movement.
Gastroenterology	The study diagnosis, and treatment of disorders of the digestive system.
Hematology/Oncology	The diagnosis and treatment of blood disorders and cancer.
Infectious Diseases	The diagnosis and treatment of infectious diseases
Neonatal/Perinatal Medicine	A subspecialty of pediatrics, concerns the care of critically ill newborn and premature infants
Nephrology	The diagnosis and treatment of kidney diseases
Pulmonology	The diagnosis and treatment of disease, conditions, and abnormalities of the lungs and cardio-pulmonary system.
Rheumatology	The diagnosis and treatment of arthritis and other rheumatic diseases that affect the joints, muscles, bones and sometimes other internal organs.

Note [a] A small number of physicians categorized as critical care include designations such as critical care surgery, critical care anesthesiology, and neonatal critical care.

1. Modeling New Entrants

The mechanism for adding new entrants to this workforce is done via the creation of a "synthetic" population based on the number and characteristics of recent graduates in each internal medicine specialty. As described in Section II B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years. The primary sources of data on new graduates are the AMA Masterfile for physicians, the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrations, and the American Board of Medical Specialties (ABMS) for physician specialties (Exhibit 32). Numbers and characteristics of new PA come from the Physician Assistant Education Association (PAEA) survey and the NCCPA for physician assistants. The number of new NPs in critical care comes from the 2012 American Association of Colleges of Nursing (AACN) survey.

After simulating the age and sex of the new entrants, the region where new providers would practice was simulated based on a model that regressed the probability of practicing in a region on the relative difference between the projected supply and demand for services in that region.

Exhibit 32: Age and Sex Distribution of New Physicians, Physician Assistants and Nurse Practitioners by Internal Medicine Specialty

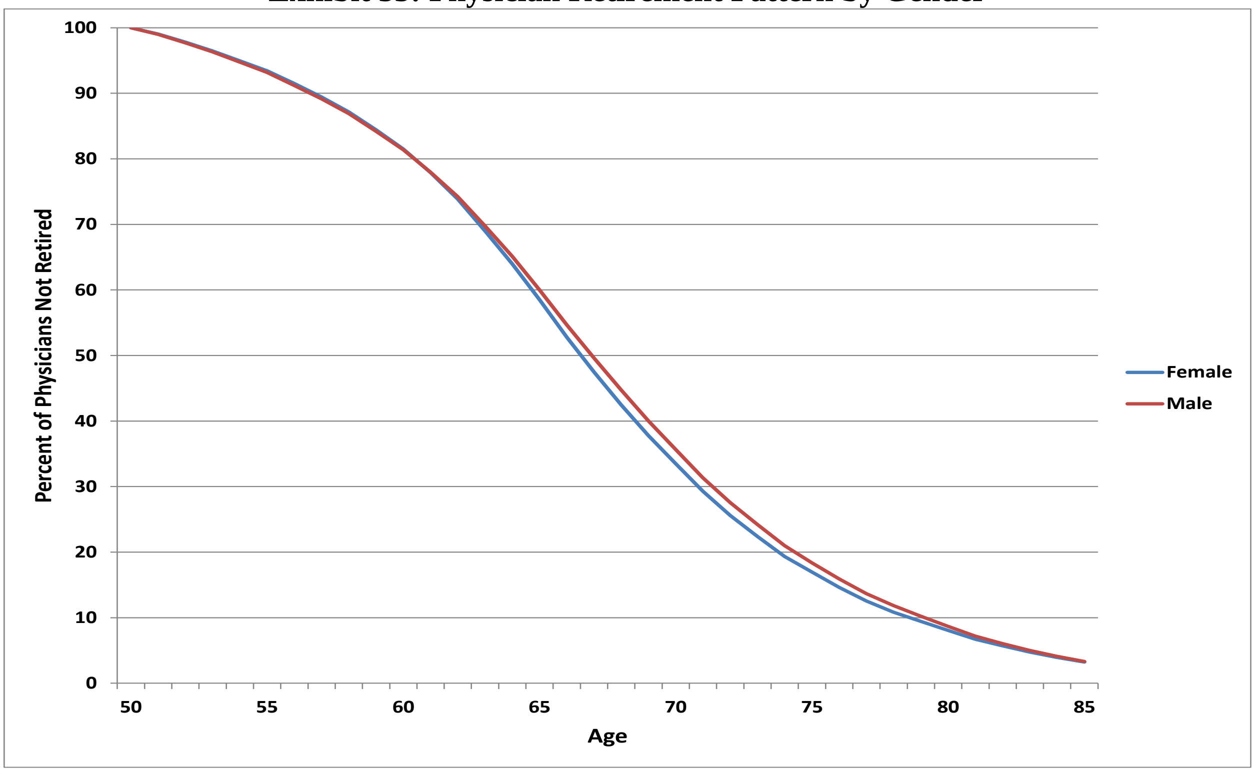
Internal Medicine Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
Physician						
Allergy & Immunology	128	63%	0%	6%	90%	4%
Cardiology	937	24%	0%	1%	91%	6%
Critical Care	249	31%	0%	1%	90%	9%
Dermatology	498	64%	0%	19%	78%	3%
Endocrinology	347	67%	0%	5%	90%	5%
Gastroenterology	530	30%	0%	1%	94%	5%
Hematology/Oncology	662	43%	0%	1%	90%	9%
Infectious Diseases	393	58%	0%	3%	92%	6%
Neonatal/Perinatal Medicine	203	63%	0%	1%	90%	9%
Nephrology	483	38%	0%	3%	88%	8%
Pulmonology	535	29%	0%	1%	91%	8%
Rheumatology	246	67%	0%	3%	89%	8%
Non-Physician Clinician						
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%
Nurse Practitioner	12,789[b]	95%	19%	47%	29%	5%

Source: 2013 AMA Master File and 2012-2013 AAMC GME Census. 2012 American Association of Colleges of Nursing (AACN) survey, 2013 NCCPA Professional Profile, Physician Assistance Education Association. [a] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs. [b] Estimates of new NPs trained reflect analysis of the 2012 NSSRN of the proportion of new NPs that work in a position requiring NP licensure.

2. Modeling Workforce Attrition

As in the case of primary care, the main source of retirement information is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey. Retirement rates differ by medical specialty; specialties such as allergy & immunology, cardiology, and gastroenterology tend to have later retirements compared to other specialties. Age-gender specific rates calculated form the Florida Bi-annual Physician Licensure Survey, were combining with the age-gender specific mortality rates to derive the overall attrition rate. Exhibit 33 shows that male and female physicians have similar attrition patterns after adjusting for the slightly higher mortality rates among men. Retirement patterns for APNs and PAs were unavailable. As a result, retirement patterns of family physicians were used as proxies.

Exhibit 33: Physician Retirement Pattern by Gender



Source: Model estimates from 2012-2013 bi-annual Florida Physician Licensure Workforce Survey and Centers for Disease Control and Prevention mortality rates by age and sex.

3. Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey of physicians in Florida who renewed their license. Analysis of Maryland's physician licensure files found similar work patterns by physician age, sex, and specialty. To generate prediction equations for hours worked patterns by physicians in a specialty, an Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable. Explanatory variables included indicators (1=yes, 0=no) for specialty, age group, female, and age-by-female interaction terms. Physicians exhibited hours worked patterns by physician age and sex as illustrated for primary care physicians (Exhibit 29). Young, male physicians tended to work more hours per week than their female counterparts, while the gender gap in hours worked largely disappeared after age 55. Hours worked patterns differed by specialty. Relative to family practice, for example, physicians in nephrology worked 13 hours more per week than dermatologists; cardiologists work 11 hours more and gastroenterologists 10 hours more per week than dermatologists. We defined 1 FTE physician for each specialty as the average hours worked per week in that specialty.

Using data on PAs working at least 20 hours per week, similar regression analyses were conducted using 2013 NCCPA license files to model hours worked patterns of PAs and the 2012 NSSRN to model hours worked patterns for critical care NPs. An FTE was defined for each occupation and specialty as the average hours worked per clinician in that occupation and specialty, using data on clinicians working at least 20 hours per week.

4. Developing Internal Medicine Subspecialties' Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demands for internal medicine physicians, and PAs were derived from the common model outlined in Section III. Prediction equations for use of office and outpatient services in medical subspecialties were estimated using Poisson regression with 2008-2012 MEPS data. Separate regressions were estimated for children and adults. The dependent variables were annual office visits and annual outpatient visits for each specialty. Explanatory variables consisted of the patient characteristics, socioeconomic and insurance variables, and health status variables described previously. The number of visits by individuals was aggregated using the sample weights in the population file to project future demand in each state.

Prediction equations for hospitalizations and ED visits used a similar approach, namely estimating a logistic regression on 2008-2012 MEPS data. Separate regressions were estimated for children and adults, and for each of the medical conditions categorized in Exhibit 34 (with categories defined by primary ICD-9 diagnosis or procedure codes). The equations predicted probabilities that each individual would have a hospitalization or ED visit for each of the condition categories. While all ED visits were assumed to involve a consultation with an emergency physician, the 2010 NHAMCS is used to identify the probability that another specialty physician provider was seen.

A single logistic regression estimated using the 2010 NHAMCS modeled the probability that an ED visit required a consulting physician. The dependent variable was whether during the visit a second physician was seen. Explanatory variables consisted of patient demographics and insurance type, and indicators variables (1=yes, 0=no) for each condition category. The assumption was made that if a visit required a consult, the consulting physician was in the medical specialty associated with the primary diagnosis code as indicated in Exhibit 34.

Exhibit 34: Hospital Inpatient and Emergency Care Service Demand Drivers by Medical Specialty

Medical Condition	ICD-9 Diagnosis and Procedure Codes	Medical Specialty	Workload Driver Modeled [a]	
			Inpatient Days	Emergency Visits
Allergy & immunology	001-139, 477, 995.3	Allergy & Immunology	Yes	NA
Diseases of the circulatory system	390-459; 745-747; 780, 785	Cardiology	Yes	Yes
NA	All hospitalization	Critical Care	Yes	NA
Diseases of the skin and subcutaneous tissue	680-709; 757; 782	Dermatology	Yes	Yes
Endocrine, nutritional and metabolic diseases, and immunity disorders	240-279; 783	Endocrinology	Yes	Yes
Diseases of the digestive system	520-538; 555-579; 751; 787; 42-54	Gastroenterology	Yes	Yes
Neoplasms, diseases of the blood & blood-forming organs	140-239, 280-289; 790	Hematology/ Oncology	Yes	Yes
Infectious and parasitic diseases	001-139, 477, 40.11, 40.3, 40.9	Infectious Diseases	Yes	Yes
Conditions originating in perinatal period	760-779	Neonatal/ Perinatal Medicine	Yes	Yes
Nephrology	580-589; 55.2-55.8	Nephrology	Yes	Yes
Disease of the respiratory system	460-519;748;786;35-39	Pulmonology	Yes	Yes
Diseases of the musculoskeletal system and connective tissue	725-729	Rheumatology	Yes	Yes

Notes: Analyzed Medical Expenditure Panel Survey (2008-2012) to model annual probability of hospitalization and annual probability of emergency department visit. Analyzed 2012 Nationwide Inpatient Sample to model average length of stay associated with each category of hospitalization. [a] Not all hospital inpatient days within a diagnosis category will necessarily require hospital rounds by a provider in that specialty, and not all emergency visits will require physician consults. NA Not Applicable

Predicted probabilities were applied on the simulated micro-data set for future years through 2025 to obtain projected service use specific to the settings where these providers work[57]. Demand for cardiologists, for example, was tied to projected demand for ambulatory visits to a cardiologist, inpatient days where the patient's primary diagnosis is cardiology related (of which a portion of days will involve hospital rounds), and emergency department (ED) visits where the patient's primary diagnosis is cardiology related (of which a portion will involve a cardiologist consult).

The HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting (Exhibit 35). These ratios were then applied to projections of future demand for services for the Baseline demand scenario in HWSM that assumes the status quo in terms of care use and delivery patterns. Estimated FTE requirements to care for each person were then aggregated to obtain the total demand for physicians.

[57] Due to small sample sizes HWSM does not model profession-setting combinations where service volume is small (e.g., physicians providing care in home health and residential facilities).

Exhibit 35: Physician FTE, Workload, & Staffing by Specialty & Care Delivery Site: 2013

	Office	Outpatient	Inpatient	Emergency
Physician FTE by Care Delivery Site[a]				
Allergy & Immunology	4,480			
Cardiology	16,540	1,070	10,120	210
Critical Care			3,570	
Dermatology	10,340	120	920	
Endocrinology	4,550	170	2,580	140
Gastroenterology	6,250	3,780	3,980	600
Hematology/Oncology	10,010	2,130	3,640	100
Infectious Diseases			8,140	280
Neonatal/Perinatal			4,820	
Nephrology	6,130	1,280	1,790	
Pulmonology	3,100	300	7,900	1,080
Rheumatology	4,540	480	280	170
Physician Workload Measures				
Allergy & Immunology	11,980,000			
Cardiology	29,021,000	1,548,000	20,691,000	3,735,000
Critical Care			183,050,000 [b]	
Dermatology	39,743,000	455,000	2,802,000	
Endocrinology	9,929,000	284,000	4,242,000	2,251,000
Gastroenterology	13,165,000	2,743,000	6,227,000	10,007,000
Hematology/Oncology	25,205,000	3,505,000	5,249,000	1,231,000
Infectious Diseases			8,491,000	4,147,000
Neonatal/Perinatal			25,558,000	
Nephrology	9,250,000	581,000	1,979,000	
Pulmonology	6,821,000	406,000	13,038,000	21,704,000
Rheumatology	7,072,000	221,000	322,000	1,923,000
Physician Staffing Ratios by Care Delivery Site				
Allergy & Immunology	2,674			
Cardiology	1,755	1,447	2,045	17,786
Critical Care			51,275 [a]	
Dermatology	3,844	3,792	3,046	
Endocrinology	2,182	1,671	1,644	16,079
Gastroenterology	2,106	726	1,565	16,678
Hematology/Oncology	2,518	1,646	1,442	12,310
Infectious Diseases			1,043	14,811
Neonatal/Perinatal			5,302	
Nephrology	1,509	454	1,106	
Pulmonology	2,200	1,353	1,650	20,096
Rheumatology	1,558	460	1,150	11,312

Sources: Total physicians based on 2013 AMA Master File. Distributions based on analysis of multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey, 2010 American Board of Internal Medicine survey, specialty-specific surveys and HWSM estimates from MEPS. The proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time. a. totals may not add up to the reported numbers in the brief due to rounding [b] All hospitalizations.

A similar process was used to estimate current and project future demand for PAs. Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each major care delivery setting and specialty. The national percentage of FTE PAs in each setting and specialty, divided by national volume of care in that setting, provided estimates of the portion of an FTE PA per unit of health care service delivered (Exhibit 36). For critical care NP, a general estimate of staffing for all NPs across all medical specialties was applied. This estimate was derived by assuming that NP distribution across settings would reflect the distribution of physicians in all medical specialties by setting.

Exhibit 36: Physician Assistant FTE by Care Delivery Site and Medical Specialty, 2013

Specialty	Provider (FTE)	Workload	Staffing Ratio
Allergy & Immunology	250	11,980,000	47,920
Cardiology	5,480	54,995,000	10,036
Critical Care[a]	2,880	183,050,000	6,067[b]
Dermatology	3,810	43,000,000	11,286
Endocrinology	420	16,706,000	39,776
Gastroenterology	1,560	32,142,000	20,604
Hematology/Oncology	1,940	35,190,000	18,139
Infectious Disease	480	8,491,000	17,690
Neonatal/Perinatal[c]			
Nephrology	370	11,810,000	31,919
Pulmonology	440	41,969,000	95,384
Rheumatology	320	9,538,000	29,806

Source: Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey. [a] Nurse Practitioner. [b] A general estimate of the staffing ratio for all NPs in medical specialties derived by weighting the total number of physician encounters across settings by the proportion of physicians FTEs serving in those setting and dividing that by the total number of NPs practicing in medical specialties in 2013 was applied. [c] Neonatal/Perinatal specialty was not modelled for PAs due to small sample size

The regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus, as well as hours worked based on provider demographics.

The demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

F. Surgical Specialty Model

Practitioners considered in this model include physicians and physician assistants (PAs) that cover 10 surgical specialties: general surgery, cardiothoracic surgery, colon/rectal surgery, neurological surgery, ophthalmology, orthopedic surgery, otolaryngology, plastic surgery, urology, and vascular surgery.

Exhibit 37: Summary of Surgical Specialties

Specialty	Description
General Surgery	Focus on organs and other structures in the abdomen.
Cardiothoracic Surgery	Involve operations on the heart, lungs, esophagus, and other organs in the chest.
Colorectal Surgery	Repair damage to the colon, rectum, and anus, caused by diseases of the lower digestive tract, such as cancer and inflammatory bowel disease.
Neurological Surgery	Involve operating on the brain, head, neck, and spinal cord.
Ophthalmology	Concern the full spectrum of eye care, from prescribing glasses and contact lenses to complex eye surgery.
Orthopedic Surgery	Focus on injuries and diseases of the musculoskeletal system including the bones, joints, ligaments, tendons, muscles, and nerves.
Otolaryngology	Focus on the medical and surgical management and treatment of patients with diseases and disorders of the ear, nose, throat, and related structures of the head and neck.
Plastic Surgery	Focus on the repair, reconstruction, or replacement of physical defects involving the skin, musculoskeletal system, maxillofacial structures, hand, extremities, and breast and trunk.
Urology	Involve diagnosis and treatment of diseases of the male and female urinary tracts, as well as the male reproductive organs.

Vascular Surgery	Encompass the diagnosis and management of disorders of the arterial, venous and lymphatic systems, exclusive of the intracranial vessels and the heart.

1. Estimating the Current Active Workforce Supply

The source for estimating the current active supply of physicians is the 2013 American Medical Association (AMA) Master File Extract. The analysis was limited to active physicians. Because the AMA file is known to misclassify older physicians who have retired as 'active', those over age 75 were deleted from the analysis file. In addition, retired physicians between 50 to 75 years of age were identified and deleted based on predicted probabilities derived from a logistic regression on age and specialty. In addition to adjusting for misclassification of retirees as active physicians, the AMA Masterfile was adjusted for undercounting hospitalists, a large proportion of who are listed under the specialty in which they received their training. The base year counts for PAs come from the 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey.

2. Modeling New Entrants

The mechanism for adding new entrants to this workforce is done via the creation of a "synthetic" population based on the number and characteristics of recent graduates in each occupation. As described in Section II B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years.

Estimates of total annual new physicians and PAs and the specialty distribution came from multiple sources. The primary sources of data on characteristics of new graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators, the 2013 AMA Masterfile and the American Board of Medical Specialties (ABMS) for physician specialties. Numbers and characteristics of new PAs come from the Physician Assistant Education Association (PAEA) and the NCCPA for physician assistants (Exhibit 38).

3. Modeling Workforce Attrition

Data sources for modeling retirement patterns of physicians by individual specialty are limited. The primary source of retirement information is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire in the upcoming five years (Exhibit 33). Age-gender specific rates calculated from the Florida Bi-annual Physician Licensure Survey, were combining with the age-gender specific mortality rates to derive the overall attrition rate. Exhibit 33 shows that male and female physicians have similar attrition patterns after adjusting for the slightly higher mortality rates among men. Retirement rates, however, differ by medical specialty. The retirement pattern for PAs was unavailable. As a result, the retirement pattern of family physicians was used as proxy.

Exhibit 38: Age and Sex Distribution of New Physicians by Surgical Specialty

Surgical Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
General Surgery	1188	36%	0%	12%	82%	6%
Cardiothoracic Surgery	97	25%	0%	0%	92%	8%
Colon/Rectal Surgery	83	36%	0%	0%	100%	0%
Neurological Surgery	149	17%	0%	5%	87%	8%
Ophthalmology	467	40%	0%	32%	66%	2%
Orthopedic Surgery	1082	11%	0%	2%	94%	4%
Otolaryngology	313	32%	0%	4%	93%	3%
Plastic Surgery	216	29%	0%	2%	93%	5%
Urology	271	25%	0%	4%	95%	1%
Vascular Surgery	122	30%	0%	1%	88%	11%
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%

Source: 2013 AMA Master File, 2012-2013 AAMC GME Census. [a] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs

4. Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey of physicians in Florida who renewed their license. An Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable in order to generate prediction equations for hours worked patterns by physicians. Explanatory variables included specialty indicators (1=yes, 0=no), age group, female, and age-by-female interaction terms. Hours worked patterns differed by specialty. Relative to family medicine, for example, physicians in neurological surgery and general surgery work 8 and 7 additional patient care hours more per week. Similar regression analysis was conducted using 2013 NCCPA license files to model hours worked patterns of PAs.

5. Developing Surgical Subspecialties' Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians and PAs was derived from the common model outlined in Section III. The HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. The consulting physician was in the surgical specialty associated with the primary diagnosis code as indicated in Exhibit 34. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting (Exhibit 40). These ratios were then applied to projections of future demand for services that assumes the status quo in terms of care use and delivery patterns.

Exhibit 39: Hospital Inpatient and Emergency Care Service Demand Drivers by Surgical Specialty

Surgical Condition	ICD-9 Diagnosis and Procedure Codes	Surgical Specialty	Workload Driver Modeled [a]	
			Inpatient Days	Emergency Visits
General surgery	860-869; 870-904; 925-939; 958-959; 996-999	General Surgery	Yes	Yes
Thoracic surgery	426, 427, 780, 785; 32.6, 34.9, 40.6, 90.4, 35-37	Cardiothoracic Surgery	Yes	NA
Colorectal surgery	17.31-17.36, 17.39, 45.03, 45.26, 45.41, 45.49, 45.52, 45.71-45.76, 45.79, 45.81-45.83, 45.92-45.95, 46.03-46.94, 153-154	Colon/Rectal Surgery	Yes	NA
Neurological surgery	850-854; 950-957; 01.0-05; 89.13	Neurological Surgery	Yes	Yes
Ophthalmology	360-379; 8-16; 95.0-95.4	Ophthalmology	Yes	Yes
Diseases of the musculoskeletal system and connective tissue; injury and poisoning	710-719; 720-724; 730-739; 805-848; 754-756; 76-84	Orthopedic Surgery	Yes	Yes
Otolaryngology	380-389; 744; 18-29	Otolaryngology	Yes	Yes
Plastic surgery	904-949; 749; 18.7, 21.8, 25.59, 26.49, 27.5, 27.69, 29.4, 31.7, 33.4, 46.4, 64.4, 78.4, 81.0-81.99, 82.7, 82.8, 83.8, 85.8, 86.84	Plastic Surgery	Yes	Yes
Diseases of the genitourinary system	590-608; 753; 788; 789; 791; 55-64	Urology	Yes	Yes
Vascular surgery	440-448; 0.4-00.5, 17.5, 35-39	Vascular Surgery	Yes	NA

Notes: Analyzed Medical Expenditure Panel Survey (2008-2012) to model annual probability of hospitalization and annual probability of emergency department visit. Analyzed 2012 Nationwide Inpatient Sample to model average length of stay associated with each category of hospitalization. [a] Not all hospital inpatient days within a diagnosis category will necessarily require hospital rounds by a provider in that specialty, and not all emergency visits will require physician consults.

Exhibit 40: Summary of National FTE Physician Distribution by Care Delivery Site and Surgical Specialty, 2013

	Office	Outpatient	Inpatient Days	Emergency
Physician FTE by Care Delivery Site[a]				
General Surgery	9,740	3,580	14,420	450
Cardiothoracic Surgery	1,050	200	150	3,100
Colon/Rectal Surgery	-	-	1,720	-
Neurological Surgery	-	-	5,110	60
Ophthalmology	16,700	1,650	80	40
Orthopedic Surgery	18,830	2,990	3,010	580
Otolaryngology	7,580	1,470	300	100
Plastic Surgery	4,690	2,400	550	90
Urology	5,750	1,070	2,740	340
Vascular Surgery			3,050	
Physician Workload Measures				
General Surgery	19,207,000	2,459,000	24,367,000	9,511,000
Cardiothoracic Surgery	294,000	19,000	34,000	7,883,000
Colon/Rectal Surgery			24,000	
Neurological Surgery			4,147,000	558,000
Ophthalmology	55,539,000	1,699,000	199,000	1,247,000
Orthopedic Surgery	63,421,000	3,536,000	10,149,000	16,219,000
Otolaryngology	20,816,000	1,201,000	596,000	3,159,000
Plastic Surgery	2,597,000	467,000	267,000	592,000
Urology	19,791,000	1,295,000	8,266,000	11,311,000
Vascular Surgery			1,337,000	
Physician Staffing Ratios by Care Delivery Site				
General Surgery	1,972	687	1,690	21,136
Cardiothoracic Surgery	280	95	227	2,543
Colon/Rectal Surgery			14	
Neurological Surgery			812	9,300
Ophthalmology	3,326	1,030	2,488	31,175
Orthopedic Surgery	3,368	1,183	3,372	27,964
Otolaryngology	2,746	817	1,987	31,590
Plastic Surgery	554	195	485	6,578
Urology	3,442	1,210	3,017	33,268
Vascular Surgery			438	

Sources: Total physicians based on 2013 AMA Master File. Distributions based on HWSM analysis of multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey, specialty-specific surveys. The proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time. [a] totals may not add up to reported totals in the brief due to rounding.

For PAs, a process similar to estimating the physician staffing ratio was used to estimate current and project future FTE demand for PAs (Exhibit 41). Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each major care delivery setting and specialty.

Exhibit 41: Summary of FTE Physician Assistant Distribution by Care Delivery Site and Surgical Specialty, 2013

Surgical Specialty	Physician Assistant (FTE)	Workload	Staffing Ratio
General Surgery	2,960	55,544,000	18,765
Neurological Surgery	2,290	4,705,000	2,055
Ophthalmology	80	58,684,000	733,550
Orthopedic Surgery	10,440	93,325,000	8,939
Otolaryngology	1,020	25,772,000	25,267
Plastic Surgery	730	3,923,000	5,374
Urology	1,610	40,663,000	25,257
Vascular Surgery	1,100	1,337,000	1,215

Source: Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey. PAs were not modeled for cardiothoracic and colon/rectal surgical specialties due to the limited data available for these disciplines.

The regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus, as well as hours worked based on provider demographics. The demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

G. Women's Health Service Provider Model

This section summarizes the methodology for projecting the supply and demand for women's health specialties including obstetrics/gynecology (OB/GYN), certified nurse midwifery (CNMs), and NPs and PAs in women's health. Selected specialties are narrow definitions of women's health that focus on biological aspects of women's health and include reproductive health and preventive care for women.

1. Estimating the Current Active Workforce Supply

The source for estimating the current active supply of obstetricians/gynecologists (OB/GYNs) is the 2013 American Medical Association (AMA) Master File Extract. The base year counts for APNs and PAs come from the 2013 National Plan and Provider Enumeration System (NPPES) and the 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey. The 2012 Association of Colleges of Nursing (AACN) survey was used to determine the number and age-sex distribution of the APN workforce in women's health, while the 2013 NCCPA professional profile survey was used the determine the age sex distribution of the PA workforce.

2. Modeling New Entrants

The mechanism for adding new entrants to the workforce each year is the creation of a "synthetic" population of the occupation based on the number and characteristics of recent graduates in each occupation. As described in Section II B, each new clinician is assigned an age and sex that reflect the distribution seen in recent years.

Estimates of total annual women's health care providers came from multiple sources. The primary sources of data on characteristics of new graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators, the 2013 AMA Master File and the American Board of Medical Specialties (ABMS) for physician specialties. Numbers and characteristics of new NPs, in the workforce entrants come from the 2012 American Association of Colleges of Nursing (AACN) survey. The 2013 NCCPA Professional Profile is the primary source for characteristics on new PA workforce entrants and the Physician Assistants Education Association the source of data on new PAs trained.

Exhibit 42: Age and Sex Distribution of New Physicians in Obstetrics/Gynecology and Certified Nurse Midwives

Women's Health	Annual Graduates	Percent Female	Age Distribution			
			<25	26-30	31-40	>41
Physicians in Obstetrics/Gynecology	1,219	81%	0%	26%	70%	4%
Certified Nurse Midwives	539	100%	2%	23%	31%	44%
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%

Source: 2013 AMA Master File, 2012-2013 AAMC GME, 2012 American Association of Colleges of Nursing (AACN) Survey. [a] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs

3. Modeling Workforce Attrition

The primary source of retirement information for physicians in HWSM is the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire in the upcoming five years. The Florida survey was used because of its large sample size and detailed information on individual specialties. Retirement patterns for Advanced Practice Nurses (APNs) and PAs were unavailable, so retirement patterns for family physicians were used as proxy for these occupations.

4. Modeling Hours Worked

Average hours worked differs by clinician age, sex, specialty, and this has an impact on the future FTE supply of providers because of the changing demographics of the health workforce. Data for modeling hours worked by physician specialty comes from the Florida 2012-2013 Bi-annual Physician Licensure Workforce Survey of physicians in Florida who renewed their license. An Ordinary Least Squares regression was conducted using physicians' reported average patient care hours per week as the dependent variable to generate prediction equations for hours worked patterns by physicians. Explanatory variables included specialty indicators (1=yes, 0=no), age group, female, and age-by-female interaction terms. Similar regression analyses were conducted using 2013 NCCPA license files to model hours worked patterns of PAs, and the 2012 National Sample Survey of Nurse Practitioners (NSSNP) for NPs, and the 2006-2012 ACS for CNMs. No sex-by-age interaction terms were included for APNs because the large majority is female.

5. Modeling Women's Health Care Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians, APNs, and PAs was derived from the common model outlined in Section III. The HWSM uses provider staffing patterns to project demand for physician specialties based on demand for health care services. Staffing patterns were calculated using the portion of national FTE providers delivering care in each setting and dividing by current national estimates of the workload driver in that work setting. These ratios were then applied to projections of future demand for services that assumes the status quo in terms of care use and delivery patterns (Exhibit 43).

For PAs, a process similar to estimating the physician staffing ratio was used to estimate current and project future FTE demand for PAs. Data from the 2013 NCCPA PA Professional Profile Survey was analyzed to provide estimates of PAs providing care in each women's health service delivery setting and specialty, and the national volume of care in each care setting and specialty, divided by the number of FTE PAs in that setting, provided estimates of PA FTE required per unit of health care service delivered in that setting.

Exhibit 43: Summary of FTE Physician and Physician Assistant in Obstetrics/Gynecology by Care Delivery Site, 2013

Obstetrics/Gynecology	Office	Outpatient	Inpatient	Emergency
FTE by Care Delivery Site				
Physicians	24,620	1,540	15,250	310
Physician Assistant	1,120	540	260	30
Workload Measures				
Physicians	79,807,000	1,493,000	11,208,000	3,327,000
Physician Assistant	79,807,000	1,493,000	11,208,000	0
Staffing Ratios by Care Delivery Site				
Physicians	3,242	969	735	10,732
Physician Assistant	71,256	2,765	43,108	--

Sources: Total physicians based on 2013 AMA Master File. Distributions based on analysis of multiple data sources: 2008-2012 MEPS, 2010 NHAMCS, 2012 NIS, 2012 Medical Group Management Association survey. Analysis of 2013 National Commission on Certification of Physician Assistants Professional Profile Survey. The proportion of physician time in non-patient care activities (e.g., research, teaching, and administration) was assumed to remain constant over time.

Demand for NPs in women's health and CNMs was tied to the total patient demand for services across settings. This was obtained by dividing the total number of NPs and CNMs by the total number of physician encounters in OB/GYN weighted by the proportion of physician FTEs serving in different settings. The regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus, as well as hours worked based on provider demographics. The demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

Exhibit 44: Summary of Advanced Practice Nurses in Women's Health Care and Workload Measures, 2013

APN Specialty	FTE Number	Total Patient Demand for Services [a, b]	Service-to-APN Ratio
Women's Health Nurse Practitioners	11,940	51,273,000	4,294
Nurse Midwives	11,110	51,273,000	4,615

Notes: [a] Patient demand for services is defined by number of encounters to physician offices, outpatient clinics, inpatient days, and emergency visits weighted by the proportion of FTE physicians delivering care in that setting.
[b]Workload driver is total encounters to offices of obstetricians &gynecologists and total inpatient days for child birth.

H. Other Medical Specialties:

This section summarizes the methodology for projecting the national supply and demand for physicians and non-physician providers: Physician Assistants (PAs) and Certified Registered Nurse Anesthetists (CRNAs) in Anesthesiology, Emergency Medicine, Neurology and Physical Medicine and Rehabilitation.

1. Estimating the Current Active Workforce Supply

The primary source for estimates of physicians currently active in the above mentioned specialties is the 2013 American Medical Association (AMA) Master File Extract. The analysis was limited to active physicians under age 75. Physician specialty was identified by using the 2013 AMA Masterfile along with the American Board of Medical Specialties (ABMS) file on physician specialties. The base year counts for CRNAs come from the 2013 National Plan and Provider Enumeration System (NPPES), while the age-sex distribution came from the 2013 ACS. The 2013 National Commission on Certification of Physician Assistants (NCCPA) Professional Profile Survey was utilized to develop the base year counts and age-sex characteristics for PAs practicing in Anesthesiology, Emergency Medicine, Neurology and Physical Medicine and Rehabilitation.

2. Modeling New Entrants

The primary sources of data on characteristics of physician graduates are the Association of American Medical Colleges (AAMC) 2012-2013 Graduate Medical Education Census completed by residency program directors and administrators. New physician graduates were assigned to Anesthesiology according to the base year proportions reported in the 2013 AMA Master File from the American Board of Medical Specialties (ABMS). Numbers and characteristics of new CRNA came from the 2012 American Association of Colleges of Nursing (AACN) survey. The Physician Assistants Education Association data was used to determine the number of new PAs trained. The 2013 NCCPA Professional Profile was used to determine the characteristics of the new PAs assuming that the distribution of PAs by different characteristics would remain the same as in the current workforce. Regional provider supplies were projected by simulating the locational choice of providers in light of the existing shortage/surplus,

Exhibit 45: Age and Sex Distribution of New Physicians, APNs and PAs

Specialty/Occupation	Annual Graduates	Percent Female	Age Distribution <25	26-30	31-40	>41
Physician Specialties						
Anesthesiology	2,174	36%	0%	18%	76%	6%
Emergency Medicine	1,754	40%	0%	35%	61%	4%
Neurology	687	44%	0%	10%	77%	13%
Physical Medicine & Rehabilitation	434	37%	0%	10%	81%	9%
Advanced Practice Nurses & Physician Assts.						
Certified Registered Nurse Anesthetist	2,493	58%	2%	40%	37%	23%
Physician Assistant	6,526 -7,353[a]	66%	3%	16%	38%	43%

2013 AMA Master File, 2012-2013 AAMC GME Census, 2012 American Association of Colleges of Nursing (AACN) survey, 2013 NCCPA Professional Profile, Physician Assistance Education Association. [b] Grows from 6,526 to 7,353 between 2013 and 2025 reflecting projected growth in number and average size of PA programs.

3. Modeling Workforce Attrition

As in the case of other specialties, physician retirement rates were calculated from the 2012 and 2013 Florida Bi-annual Physician Licensure Survey which asks active physicians about their intention to retire. This data was compared to the AAMC's 2006 Survey of Physicians over Age 50 which collected information on age at retirement or age expecting to retire. Both sources showed similar retirement rates. However, the Florida survey had a larger sample size and more detailed individual specialties. Retirement rates were combined with the age-gender specific mortality rates adjusted downward to reflect the lower mortality of healthcare workers.[58] Emergency medicine, anesthesiology, and radiology showed earlier retirement rates compared to physicians in other specialties. Retirement pattern for family physicians was used as proxy for retirement rates of PAs and CRNAs.

4. Modeling Hours Worked

Ordinary Least Squares regressions were conducted for each occupation using reported average hours worked per week as the dependent variable and age group, gender and age-gender interaction as explanatory variables. For physicians, data from the Florida 2012-2013 bi-annual Physician Licensure Workforce Survey (n=18,016) file of physicians was used. Hours worked patterns differed by specialty. An FTE was defined for each specialty as the average number of patient care hours worked in that specialty.

Similar regression analyses were conducted using 2013 NCCPA Professional Profile Survey to model hours worked patterns of PAs and the 2006-2012 ACS to model hours worked patterns of

[58] Johnson NJ, Sorlie PD, Backlund E. The impact of specific occupation on mortality in the US National Longitudinal Mortality Study. Demography; 1999 Aug; 36:355-367.

CRNAs. An FTE was defined for each occupation as the average hours worked per clinician in that occupation and specialty, using data on clinicians working at least 20 hours per week.

5. Modeling Demand Projections

Consistent with the approach adopted for other health occupations modeled, the projected demand for physicians, CRNAs and PAs was derived by applying the predicted probabilities for each demographic group estimated from MEPS data on the simulated micro-data set for future years derived from the Census Bureau to obtain projected service use specific to the settings where these providers work. Using logistic regression, and the appropriate ICD9 codes (320-359, 742, 781, 784, 800-804 for neurology; 0.4-00.5, 17.5, 35-39; 93 for Physical Medicine and Rehabilitation services), prediction equations for office visits, inpatient days and emergency room visits for each type of provider were developed with 2008-2012 MEPS data. Separate regressions were estimated for children and adults.

Prediction equations for ED visits used a similar approach, but did not use ICD9 codes. Instead, all ED visits were assumed to involve a consultation with an emergency physician. Because MEPS lists only the highest level of provider seen, the 2010 NHAMCS is used to identify the probability that a PA was also seen. Provider demand in anesthesiology was determined by the demand for all surgical procedures across all settings. The predicted probabilities of service use by demographic groups when applied to the future population predicted the workload of the different occupations.

Exhibit 46 provides the staffing ratio for each type of service was derived by dividing the current volume of services by the number of provider FTE who currently provide these services and applied to the projected service demand to obtain the predicted demand for provider FTE.

Exhibit 46: Summary of FTE Physician Distribution by Care Delivery Site, 2013

	Office	Outpatient	Inpatient	Emergency	Other[a]	Total
Workload Measures						
Anesthesiology [b]						21,205885
Emergency Medicine				118,570,000		
Neurology	13,996,000	642,000	3,139,000	5,233,000	316,439,000	
Physical Medicine and Rehabilitation	3,307,000	326,000	621,000		316,439,000	
Physician Distribution by Care Delivery Site in FTE						
Anesthesiology						45,940

Emergency Medicine				39,340		39,340
Neurology	10,630	1,720	3,270	490		16,110
Physical Medicine and Rehabilitation	8,430	830	1,580			10,840
Physician Staffing Ratios						
Anesthesiology						462
Emergency Medicine				3,014		
Neurology	1,317	373	960	10,680		
Physical Medicine and Rehabilitation	392	393	393			
Physician Assistant Distribution by Care Delivery Site						
Anesthesiology						750
Emergency Medicine				13,800		
Neurology	430	220	200		20	870
Physical Medicine & Rehabilitation	510	150	100		170	930
Physician Assistant Staffing Ratio						
Anesthesiology						28,274
Emergency Medicine				11,917		
Neurology	32,549	2,918	15,695		15,821,000	
Physical Medicine & Rehabilitation	6,484	2,173	6,210		1,861,405	
Nurse Anesthetists						44,660
Nurse Anesthetist Staffing Ratio						474

Source: 2013 AMA Masterfile, 2013 National Plan and Provider Enumeration System (NPPES) and 2013 NCCPA Professional Profile, Physician Assistance Education Association; [a] Other category includes long term care, school health, home and hospice, and all other settings; Workload driver is the size of the population. [b] Workload driver is defined by the total outpatient and inpatient surgical procedures.

The regional provider demand estimates were derived by pro-rating the national demand for health care services based on the population characteristics of the regions (e.g., age, sex, household income, insurance status, health status, etc.).

I. Health Care Support and Technical Occupations' Model

This section summarizes the methodology for projecting the national supply and demand for health care support and technical occupations. Because of data limitations, projections could only be made for five support and technical occupations: optometrists and opticians, physical and occupation therapists, and pharmacists.

1. Estimating the Base Year Workforce Supply

The base year counts for the occupations in this section came from pooled 2006-2011 ACS. When small sample size in ACS resulted in unreliable estimates, information from BLS' Occupational Employment Statistics (OES) was used to calibrate ACS data. Data from multiple years of the ACS were pooled and calibrated to 2012 national estimates to provide more stable estimates of the age and sex distribution of workforce. Because these occupations were projected only at the national level, no other characteristics were attached to the ACS data file.

2. Modeling New Entrants

The primary source for estimating annual numbers of new entrants in each occupation was the 2010 Integrated Postsecondary Education Data System (IPEDS). As described in Section II B, new entrants were added to the workforce via a "synthetic" cohort. The size of the cohort was based on the number and characteristics of recent graduates in each occupation. Each new worker was assigned an age and sex that reflected the distributions seen in recent years (Exhibit 47). The number of new entrants and their age-sex distribution were assumed to remain constant during the projection period. Supply projections were not made for a number of healthcare support occupations and technicians because the high turnover rates in these occupations make the supply forecast unreliable.

Exhibit 47: Age and Sex Distribution of New Entrants to Health Care Support and Technical Occupations

Occupation	Annual Graduates	Female (%)	Age Distribution (%)			
			≤25	26-30	31-40	≥41
Behavioral Health Services						
Psychologists	5,744	68	5	71	22	2
Diagnostic Services						
Diagnostic medical sonographers	Not Estimated					
Medical and clinical laboratory technicians	Not Estimated					
Medical and clinical laboratory technologists	Not Estimated					
Nuclear medicine technologists	Not Estimated					
Radiologic technologists	Not Estimated					
Dietary and Nutrition Services						
Dietitians and nutritionists	3,526	96	64	16	14	6
Direct Care Services						
Home health aides	Not Estimated					
Nursing assistants	Not Estimated					
Pharmacy Occupations						
Pharmacists	12,346	62	63	18	14	6
Pharmacy technicians	Not Estimated					
Pharmacy aids	Not Estimated					
Rehabilitation Services						
Occupational therapists	4,477	92	64	17	14	6
Physical therapists	7,423	68	72	13	11	4
Occupational therapy assistants	Not Estimated					
Physical therapy assistants	Not Estimated					
Respiratory Care Services						
Respiratory therapist	8,116	69	26	24	32	19
Respiratory therapy technicians	Not Estimated					
Therapeutic Services						
Chiropractor	2,601	37	32	57	12	0
Podiatrists	537	42	5	69	24	2
Vision Services						
Opticians	880	67	47	19	19	15
Optometrists	1,404	39	5	70	23	2

Source: 2010 IPEDS.

3. Modeling Workforce Participation

Using data from 2006-2011 ACS, the age-sex specific probability that individuals would remain active in their occupation was estimated by occupation similar to the approach used for modeling nurse supply. For those over age 50, retirement patterns by age and sex reflect retirement patterns by highest level of educational attainment. Since many of the health care support and technical occupations showed representation from multiple educational groups, weights were created in HWSM that blended the proportions of workers in each category to reflect the attrition rate for those over age 50 (Exhibit 48). The predicted probabilities were applied to the starting year supply of professionals in those occupations to simulate individuals who were expected to leave the occupation over the year.

Exhibit 48: Highest Educational Attainment in Health Care Support and Technical Occupations

	2006-2011 American Community Survey Data on Education Distribution of Current Workforce (%)			HWSM Weights for Blending Workforce Participation Rates		
Occupation	**Less than Baccalaureate**	**Baccalaureate**	**Graduate**	**Less than Baccalaureate**	**Baccalaureate**	**Graduate**
Behavioral Health Services						
Clinical psychologists	0%	2%	98%			100%
Diagnostic Services						
Diagnostic medical sonographers	Not Estimated					
Medical and clinical laboratory technicians	Not Estimated					
Medical and clinical laboratory technologists	Not Estimated					
Nuclear medicine technologists	Not Estimated					
Radiologic technologists	Not Estimated					
Dietary and Nutrition Services						
Dietitians and nutritionists	35%	37%	28%	35%	37%	28%
Direct Care Services						
Home health aides	Not Estimated					
Nursing assistants	Not Estimated					
Pharmacy Occupations						
Pharmacists	6%	44%	50%	6%	44%	50%
Pharmacy technicians	Not Estimated					
Pharmacy aids	Not Estimated					
Rehabilitation Services						
Occupational therapists	10%	54%	36%		60%	40%
Physical therapists	11%	41%	48%		46%	54%
Occupational therapy assistants	Not Estimated					
Physical therapy assistants	Not Estimated					
Respiratory Care Services						
Respiratory therapists	72%	23%	4%	76%	24%	
Respiratory therapy technicians	Not Estimated					
Therapeutic Services						
Chiropractors	3%	3%	94%			100%
Podiatrists	1%	2%	97%			100%
Vision Services						
Opticians	84%	14%	3%	100%		
Optometrists	2%	1%	97%			100%

Source: 2006-2011 ACS

4. Modeling Hours Worked

For the occupations for which supply projections were made, data from 2006-2011 ACS were used to derive the number of hours each individual spent in professional activities. Explanatory variables included age, sex, unemployment rate, and expected hourly earnings. The BLS estimates of the average wage for each occupation and the overall unemployment rate in each year were incorporated in the model so that wages and unemployment rates varied by year. The number of hours per week worked for future years was simulated for each individual by applying the expected number of hours for each age and sex cohort. The hours for each individual was divided by the average hours worked by professionals in the occupation in the base year to estimate the FTE supply in future years.

The supply projections for health care support and technical occupations were made under the basic assumption that the current patterns of retirement and hours worked would remain unchanged within a given age and sex group, and that the current number of new entrants to the occupation would remain constant.

5. Developing Health Care Support and Technical Occupations' Demand Projections

The projected demand for professionals in health care support and technical occupations was derived from the common model estimated on the baseline population and health care usage as outlined in Section III B. Demand for health care services was projected under the assumption that recent patterns of care use and delivery would remain unchanged. Predicted probabilities were applied on the simulated micro-data set for future years to obtain projected health care service use specific to the settings where these professionals are employed. Demand for physical and occupational therapists who often visit people in their homes were tied to demand for home health visits, in addition to nursing home stays, and office visits; demand for pharmacist was tied to number of prescriptions written during patient visits to provider offices, out-patient clinics, and EDs, according to BLS distribution (see Appendix, Exhibit A-1). Data on the number of medications prescribed from the 2010 NAMCS, NHAMCS and NIS were used to model the number of prescriptions that an individual would receive. These were aggregated for the entire population.

The number of health workers employed in a setting in the base year was assumed to reflect demand for services in that setting. Therefore, projections of future demand for providers were based on the 2012 ratio of providers to services. The information on the distribution of employment across care settings came from the May 2012 OES. Exhibit A-1 in the Appendix provides detailed data on employment setting, workload and staffing-ratios by provider type.

J. Dental Health Care Provider Model

This section contains a description of the data, assumptions, and methods used to adapt the HWSM to model the supply of and demand for dentists and dental hygienists. Projections for these oral health professionals were developed at the state level and then aggregated to obtain the national projections.

1. Estimating the Base Year Workforce Supply

The first step to modeling the future dental health workforce at the state level was to obtain an estimate of the number and characteristics of dental health providers in each state in the base year (2012). For dentists, this data came from the American Dental Association's (ADA) 2010 Master File calibrated to published statistics from the 2012 Master File.[59] The Master File contains information on every individual who completed dental school. Base year supply estimates for dental hygienists came from the ACS. ACS data files for 2006 through 2011 were combined to obtain stable state-level estimates. The sample weights in the ACS were re-scaled such that the aggregate data file was representative of the 2012 national population. The individual records that contained information on age, sex, and state of residence from the ACS and the ADA were retained as the base year supply of active dental health professionals, but were assigned adjusted weights as described above.

2. Modeling New Entrants

The number of new dentists entering the workforce each year increases gradually from about 5,000 in 2012[60] to 5,500 by 2020. The increase reflects new schools opening and program expansions that have been announced to take place by 2020. The number of new entrants then remains constant through 2025. Age, sex, and state of residence data on dentists who had graduated in 2008 and 2009 from the 2010 ADA Master File were used to project the age, sex and state of residence of new dentists. The 2010 IPEDS was used to determine the number of dental hygienists which was assumed to remain constant at 8,000 annual entrants through 2025. The age and sex distribution of dental hygienists were derived from NCES[61] (Exhibit 49).

[59] At the time the model was being developed, NCHWA did not have access to the 2012 ADA Master File.

[60] American Dental Association. 2010-2011 Survey of Dental Education Series, 2012. http://www.ada.org/en/science-research/health-policy-institute/data-center/dental-education

[61] National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Postsecondary Education. Digest of Education Statistics 2012. http://nces.ed.gov/pubs2014/2014015.pdf

Exhibit 49: Age and Sex Distribution of Annual New Entrants to Oral Health Occupations

Occupation	Estimated Number	Female (%)	Age Distribution (%)			
			≤25	26-30	31-40	≥41
Dentists (generalists and specialists)	5,000-5,500	46	5	69	24	2
Dental hygienists	8,000	97	47	21	20	12

Sources 2010-2011 Survey of Dental Education for estimated number and 2010 ADA Master File for age and sex distribution of dentists; 2009-2010 IPEDS for estimated number and 2012 National Center for Education Statistics (NCES) for age and sex distributions of dental hygienists

The ADA 2010 Master File data suggested that 46 percent of new dentists were female. In contrast, 97 percent of new dental hygienists were female. HWSM assumed that the age and sex distribution of new oral health professionals remained the same in the future. Because microsimulation requires individual level data, individual records of future dentists and dental hygienists were simulated using the age and sex distributions in Exhibit 49. After simulating the age and sex of the new entrants, the state where new dental health providers would practice was simulated based on a model that regressed the probability of practicing in a state on the relative difference between the projected supply and demand for dental services in that state.

3. Modeling Workforce Participation

The workforce participation rates for dental health occupations are calculated as the number of persons in the occupation who are *active in the labor force* divided by the *total number of persons in that occupation*. Because ACS only lists the occupations of individuals who have been in the workforce sometime during the past five years, it was necessary to account for those in the occupation who had been retired for more than five years in the denominator. It was assumed that few dentists and dental hygienists under age 50 would have stopped practicing their occupation for more than five continuous years. Therefore the denominator was estimated directly from ACS data on occupation for individuals under age 50. For individuals over age 50, it was initially assumed that their work force participation rates would mirror the participation rates of individuals in their education group and the denominator was calculated on the basis of their highest educational attainment (less than baccalaureate, baccalaureate, or graduate degree) of those individuals who have been employed at some time during their adult life. Since an overwhelmingly large proportion of dentists possess graduate degrees, the activity rate of individuals with graduate degree was used for activity rates for dentists over age 50 (Exhibit 50). For dental hygienists over age 50, a blended labor force participation rate for persons with a baccalaureate degree and those with less than a baccalaureate degree was used—reflecting the fact that approximately two-thirds of hygienists have less than a baccalaureate degree and one third have a baccalaureate degree. The group of dental hygienists with graduate degrees was too small to obtain reliable estimates, and was folded in one of the other groups.

Exhibit 50: Highest Educational Attainment by Oral Health Occupation

Occupation	Education Distribution of Current Workforce (%)			HWSM Weights for Blending Workforce Participation Rates (%)		
	Less than Baccalaureate	Baccalaureate Degree	Graduate Degree	Less than Baccalaureate	Baccalaureate Degree	Graduate Degree
Dentist	1	1	98	0	0	100
Dental hygienists	65	31	5	68	32	0

Source: 2006-2011 ACS

Further analysis based on the age distribution of oral health providers suggested that dentists have slightly earlier retirement relative to patterns for people with a graduate degree, so age-specific activity rates for dentists were re-scaled to adjust for this difference. Likewise, analysis of the age distribution of dental hygienists suggested that they retire at rates slightly faster than others with similar levels of education. Adjustments were made in the age pattern of dental hygienists' activity rates to reflect the faster retirements.

4. Modeling Hours Worked

Equations describing weekly work patterns came from Ordinary Least Squares regressions from 2006-2011 ACS data. One regression equation estimated hours worked by dentists[62], and a separate regression modeled hygienists' hours worked. The dependent variable in the estimating equation was the log of hours worked in the previous week, and explanatory variables included age group, sex, log of expected hourly earnings, state-level estimate of the overall unemployment rate, and a year indicator. Wages and unemployment rates were introduced as time varying covariates and were derived from the BLS state-level estimates for each of the years between 2006 and 2011. The expected number of hours worked by each individual was converted to FTE supply by dividing the total person-hours worked by the average number of hours worked per week in the base year by dentists (37 hours) and dental hygienists (29 hours).

[62] The regression included orthodontists.

5. Modeling Dental Health Workforce Demand

To adapt HWSM to oral health services, MEPS Dental Visit Files from 2007-2011 were analyzed. Information on two types of visits was extracted from MEPS Dental Visit Files: 1) dental visits for acute or preventive care; and, 2) visits for dental cleanings.

Poisson regressions for each type of service visits were estimated for adults and children separately. Explanatory variables included the demographic, economic, health status, and health behavior variables described earlier for modeling other health occupations. These regressions were used to derive the expected numbers of the two types of visits for every individual. The number of visits by individuals was then aggregated using the sample weights in the population file to project future demand in each state.

Data limitations precluded the inclusion of dental insurance as a determinant of the demand for services. Therefore, the influence of dental insurance on use of oral health services is reflected in the regression intercept and other explanatory variables such as presence of medical insurance (which is likely positively correlated with having dental insurance).

The simulated demand for dental services was translated to demand for providers through the national provider-to-visit ratios. Because dental service is delivered mainly in a clinic setting, staffing ratios by other settings were not developed. HWSM assumed that the national demands for oral health services in the base year were met exactly by the base year supply of providers for the purpose of determining the provider to visit ratios (Exhibit 51). However, given that visits modeled from MEPS data only captured met demand, combined with the recognized shortage of dentists in Dental Health Professional Shortage Areas (DHPSA), the demand for dentist FTE in the base year was augmented by 7,014, the number needed to de-designate DHPSAs.[63]

It was assumed that the provider-to-visits ratio would remain unchanged during the projection period and oral health service delivery in each state followed the national patterns controlling for population characteristics. National ratios of dentists-to-dental visits (excluding teeth cleaning) in the base year were applied to the projected visits to determine the future demand for dentists; the ratio of dental hygienists-to-teeth cleaning visits were applied to project the future demand for dental hygienists.

[63] HRSA estimated that 7,101 dentists are needed to de-designate DHPSAs in 2012, including 87 dentists in Puerto Rico and U.S. territories.

Exhibit 51: Summary of Dentist and Dental Hygienist Workload Drivers: 2012

Provider Type	Estimated Providers[1]	Estimated Visits[2]	Provider to Visit Ratio
Dentists	190,800	215,700,000	1:1,130
Dental hygienists	153,600	285,200,000	1:1,860

Source: [1] ADA 2010; [2] and MEPS 2007-2011 applied to 2012 population.

V. HWSM Validation, Strengths, and Limitations

This section summarizes activities undertaken to validate HWSM and discusses the strengths and limitations of the model.

A. HWSM Validation

A model, by definition, is a simplified version of reality. Validation activities are important to help ensure that the model reflects reality as accurately as possible. Validation of HWSM is a continual process. As different health professionals are accommodated and the model is updated with the new data, validation activities will continue.

Following International Society for Pharmacoeconomics and Outcomes Research (ISPOR) guidelines on best practices, validation activities in HWSM included the following:[64]

- **Review by subject matter experts (face validity)**. *The model framework should conform to observations about how the system works, and be consistent with theory. Expert review also helps ensure that the model uses the best available inputs and parameters. Model outputs should be consistent with expectations of subject matter experts*.

  The model framework was approved by a technical evaluation panel consisting of experts in health care workforce at HRSA. The modeling approach was selected because it is particularly useful for analyzing complex systems such as the health care system, where decision-making is decentralized and autonomous. For supply modeling, each individual makes his or her career and labor force participation decisions based on their own unique characteristics and in response to external factors such as earnings potential and unemployment risks. For demand modeling, decisions to use health care services are made by individuals depending upon their health risks and financial constraints. HWSM has the

[64] Eddy DM, Hollingworth W, Caro JJ, Tsevat J, McDonald KM, Wong JB. 2012."Model transparency and validation: a report of the ISPOR-SMDM Modeling Good Research Practices Task Force—7." *Value Health*;15(6):843-850.

potential to capture the complex dynamic interactive processes that characterize the demand for and supply of health care providers.

The model makes use of the most recent data available to date and can be updated with new data as it becomes available without changing the basic features of the model.

The outputs from the nursing model have been verified by an established researcher in the area of health workforce.[65]

- **Internal validation (verification)**. *This set of activities involved reviewing computer code for accuracy, validating parameters in the model against their source, and putting HWSM through a "stress test" by modeling extreme input values to test whether the model produces expected results.*

  Internal validation activities have been conducted on all parts of the model used to forecast supply and demand for oral health, nursing, and the cross-occupation occupations. Regression coefficients were examined to flag unrealistic estimates and results were examined to ensure that state-level estimates add up to national estimates.

- **External and predictive validation**. *This form of validation was used to identify external data sources (not used in model development) for comparison to model outputs*.

  As an example, the health-related characteristics of the baseline population data base created in HWSM were calibrated by comparing the prevalence estimates to published U.S. Centers for Medicare and Medicaid Services (CMS) and the most recent American Health Care Association (AHCA) resident counts in each state. Similarly, the expected numbers of home health visits generated by HWSM were compared to the results from the latest version of the National Home and Hospice Care Survey (NHHCS). Validation and calibration activities were conducted on the labor force participation rates which included developing preliminary supply projections to determine if the base year age distribution of the workforce was consistent with labor force retirement patterns. In addition, information from occupational associations and other sources were used to validate the model inputs.

- **Between-model validation (cross validation)**. *This type of validation compared model outputs with results of other models.*

[65] Personal communication, Dr. Thomas Ricketts.

The cross-model comparisons made thus far have compared HWSM projections with the BLS 10-year (2012 to 2022) employment forecasts for select occupations. The BLS forecasts are based on two major components: (1) employment opportunities due to demand growth; and, (2) employment needs to replace people who have left the labor force. HWSM produces similar outputs. HWSM and BLS projections are relatively similar despite using very different modeling approaches, data, and assumptions. Results from published articles[66,67] on nursing supply were also used to validate the HWSM projections on the nursing workforce.

B. HWSM Strengths and Limitations

The main strengths of HWSM are the use of recent data sources and a sophisticated microsimulation model for projecting health workforce supply and demand. Compared to population-based approaches, this approach has a number of advantages:

- More predictive variables can be used in modeling, which enhances the accuracy of results.
- Lower levels of geography can be modeled, which meets HRSA's goal of building more accurate state level projections.
- Projection models can be easily consolidated across occupations, with occupation-specific equations integrated into a single platform.
- The modular approach in HWSM allows for refinements and improvements to be carried out in sub-components of the model.

HWSM uses individuals as the unit of analysis. This level of analysis creates flexibility for incorporating changing prevalence of certain chronic conditions or health-related behaviors and risk factors into demand estimations. HWSM also provides added flexibility for modeling the workforce implications of changes in policy (such as expanded health insurance coverage under the ACA).

Many of the limitations of HWSM stem from current data limitations. For example, HWSM uses the ACS to estimate current supply of many health occupations, although many states have access to more complete supply data collected through the licensure/certification processes. On the demand side, one limitation of the BRFSS as a data source is that as a telephone-based survey, it tends to exclude people who may not have their own telephone.

[66] Auerbach, D. I., Buerhaus, P. I. & Staiger, D. O. 2014. "Registered nurses are delaying retirement, a shift that has contributed to recent growth in the nurse workforce." *Health Affairs*, 33(8):1474-1480.

[67] Auerbach, D. I., Buerhaus, P. I. & Staiger, D. O. 2011. "Registered nurse supply grows faster than projected amid surge in new entrants ages 23-26." *Health Affairs*, 30(12):2286-2292.

Other current data limitations associated with HWSM include the following:

1. There is little information on the influence of provider and payer networks on demand and consumer care migration patterns.
2. Data is currently lacking to estimate demand and adequacy of supply at the state and sub-state levels for many health occupations. While the ACS is available as a substitute for detailed demographic information, it is unable to identify occupations to the six-digit Standard Occupational Classification level. Furthermore, counts of the current level of an occupation are more precise when taken from licensing data instead of estimates from either the ACS or the OES.
3. On the demand side, there is a paucity of information on how care delivery patterns might change over time in response to the ACA and other emerging market factors.
4. Due to lack of data, it is not possible to identify services received in certain specialized settings such as ambulatory surgical units.

Appendix

Exhibit A- 1: Summary of Workload Measures and Staffing Ratios for Health Care Support and Technical Occupations

Health Workforce Distribution (N) by Delivery Site										
Occupation	Total	Delivery Sites								
		Ambulatory	Emergency	Inpatient	Home Health	Nursing Home	Public Health	School Health	Education	Other
Behavioral Health Services										
Psychologists	100% (188,300)	100% (188,300)								
Diagnostic Services										
Diagnostic medical sonographers	100% (58,000)	38% (21,771)		61% (35,616)					1% (613)	
Medical and clinical laboratory technicians	100% (161,500)	20% (32,300)	5% (8,075)	75% (121,125)						
Medical and clinical laboratory technologists	100% (164,300)	20% (32,860)	5% (8,215)	75% (123,225)						
Nuclear medicine technologists	100% (20,900)	31% (6,386)		68% (14,243)					1% (271)	
Radiologic technologists	100% (194,790)	34% (66,139)		64% (123,862)			2% (4,788)			
Dietary and Nutrition Services										
Dietitians and nutritionists	100% (67,400)	18% (12,097)		35% (23,703)	2% (1,392)	11% (7,394)	20% (13,162)	2% (1,685)		12% (7,967)
Direct Care Services										
Home health aides	100% (839,930)				100% (839,930)					
Nursing assistants	100% (1,420,020)	7% (97,350)		26% (371,080)	5% (63,490)	55% (786,660)				7% (101,440)
Pharmacy Services										
Pharmacists	100%	78%	22%							

Health Workforce Distribution (N) by Delivery Site										
		Delivery Sites								
Occupation	**Total**	**Ambulatory**	**Emergency**	**Inpatient**	**Home Health**	**Nursing Home**	**Public Health**	**School Health**	**Education**	**Other**
	(264,100)	(206,451)	(57,649)							
Pharmacy technicians	100% (334,400)	84% (280,730)	16% (53,670)							
Pharmacy aids	100% (42,600)	95% (40,380)	5% (2,220)							
Rehabilitation Services										
Occupational Therapists	100% (86,286)	26% (22,780)		38% (32,444)	11% (9,319)	11% (9,319)		14% (12,425)		
Physical Therapists	100% (191,563)	46% (87,353)		34% (64,365)	12% (23,754)	8% (16,091)				
Occupational therapy assistants	100% (29,500)	46% (13,548)		18% (5,272)	6% (1,643)	24% (7,026)		7% (2,011)		
Physical therapy assistants	100% (76,492)	46% (35,309)		32% (24,164)	9% (7,160)	13% (9,860)				
Respiratory Care Services										
Respiratory therapists	100% (104,086)	19% (19,755)	44% (46,290)	37% (38,018)	0.02% (23)					
Respiratory therapy technicians	100% (13,460)	19% (2,555)	44% (5,986)	37% (4,916)	0.02% (3)					
Therapeutic Services										
Chiropractor	100% (58,800)	100% (58,800)								
Podiatrists	100% (10,700)	100% (10,700)								
Vision Services										
Optometrist	100% (36,260)	100% (36,260)								
Opticians	100% (54,500)	100% (54,500)								

Source: May 2012 Occupational Employment Statistics and HWSM baseline results

Health Workforce Workload by Care Delivery Site									
Occupation	**Delivery Sites (Units)**								
	Ambulatory (Visits)	***Emergency (Visits)***	***Inpatient (Days)***	***Home Health (Visits)***	***Nursing Home (Population)***	***Public Health (Population)***	***School Health (Population)***	***Education (Trainees)***	***Other (Population)***
Behavioral Health Services									
Psychologists	5,726,228								
Diagnostic Services									
Diagnostic medical sonographers	957,824,918		171,483,258					Not Estimated	
Medical and clinical laboratory technicians	957,824,918	113,437,741	171,483,258						
Medical and clinical laboratory technologists	957,824,918	113,437,741	171,483,258						
Nuclear medicine technologists	3,208,056		34,404					Not Estimated	
Radiologic technologists	3,208,056		34,404			314,004,465			
Dietary and Nutrition Services									
Dietitians and nutritionists	957,824,918		171,483,258	65,361,194	19,173,536	314,004,465	58,004,764		314,004,465
Direct Care Services									
Home health aides				34,887,385					
Nursing assistants	1.002,118,228	113,437,258	171,483,258	4,477,903	19,173,536				314,004,465
Pharmacy Services (Prescriptions)									
Pharmacists	1,955,699,897	224,332,952							
Pharmacy technicians	1,955,699,897	224,332,952							
Pharmacy aids	1,955,699,897	224,332,952							
Rehabilitation Services									
Occupational Therapists	1,840,597		680,697	310,041	19,173,536		58,004,764		
Physical Therapists	60,755,485		680,697	745,589	19,173,536				

Health Workforce Workload by Care Delivery Site									
Occupation	Delivery Sites (Units)								
	Ambulatory (Visits)	*Emergency (Visits)*	*Inpatient (Days)*	*Home Health (Visits)*	*Nursing Home (Population)*	*Public Health (Population)*	*School Health (Population)*	*Education (Trainees)*	*Other (Population)*
Occupational therapy assistants	1,840,597		680,697	310,041	19,173,536		58,004,764		
Physical therapy assistants	60,755,485		680,697	745,589	19,173,536				
Respiratory Care Services									
Respiratory Therapists	11,389,732	21,660,663	15,446,529	21,525					
Respiratory therapy technicians	11,389,732	21,660,663	15,446,529	21,525					
Therapeutic Services									
Chiropractors	57,275,468								
Podiatrists	12,437,351								
Vision Services									
Optometrists	24,732,085								
Opticians	24,732,085								

Source: HWSM baseline results

Health Workforce Staffing Ratios by Care Delivery Site									
Occupation	Delivery Sites (Units per Provider)								
	Ambulatory (Visits)	*Emergency (Visits)*	*Inpatient (Days)*	*Home Health (Visits)*	*Nursing Home (Population)*	*Public Health (Population)*	*School Health (Population)*	*Education (Trainees)*	*Other (Population)*
Behavioral Health Services									
Psychologists	30								
Diagnostic Services									
Diagnostic medical sonographers	43,996		4,815						
Medical and clinical laboratory technicians	29,654	14,048	1,416						
Medical and clinical laboratory technologists	29,149	13,809	1,392						
Nuclear medicine technologists	502		2						
Radiologic technologists	49					65,575			
Dietary and Nutrition Services									
Dietitians and nutritionists	79,178		7,235	46,947	2,593	23,857	34,430		39,412
Direct Care Services									
Home health aides				42					
Nursing assistants	10,294		462	71	24				3,095
Pharmacy Services (Prescriptions)									
Pharmacists	9,473	3,891							
Pharmacy technicians	6,966	4,180							
Pharmacy aids	48,432	101,051							
Rehabilitation Services									
Occupational Therapists	81		21	33	2,057		46,68		
Physical Therapists	696		11	31	1,192				
Occupational therapy assistants	136		129	189	2,729		28,847		
Physical therapy assistants	1,721		28	104	1,945				
Respiratory Care Services									
Respiratory therapists	577	468	406	942					
Respiratory therapy technicians	4,458	3,619	3,142	7,287					
Therapeutic Services									
Chiropractors	974								

Health Workforce Staffing Ratios by Care Delivery Site									
Occupation	**Delivery Sites (Units per Provider)**								
	Ambulatory (Visits)	***Emergency (Visits)***	***Inpatient (Days)***	***Home Health (Visits)***	***Nursing Home (Population)***	***Public Health (Population)***	***School Health (Population)***	***Education (Trainees)***	***Other (Population)***
Podiatrists	1,162								
Vision Services									
Optometrists	682								
Opticians	454								

Source: May 2012 Occupational Employment Statistics and HWSM baseline results